# Social Media and Humanitarian Operations: Measuring the Impact of Social Media during the 2016 Fort McMurray Wildfires on stakeholder's actions

Aleem Damji
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## Introduction

As a vehicle through which countless people can form communities, exchange information, and influence decisions, social media has often found itself in the center of many studies across almost every field of research. In the field of humanitarian relief operations, where challenges are characterized by high urgency and a large amount of uncertainty, social media has not been studied exhaustively. This presents an opportunity to delve into the impact of social media on humanitarian operations.

Humanitarian operations have increased their usage of social media, both in crisis and non-crisis periods. This raises questions as to what the role of social media is in a humanitarian crisis and how it affects both the operations of a humanitarian organization and the interactions between the organization and other stakeholders.

In this report, the Canadian Red Cross' usage of social media during the 2016 Fort McMurray fires is examined. Specifically, the Red Cross' social media usage is empirically examined and quantified, especially its impact on the online and offline activities of various stakeholders.

The Canadian Red Cross were chosen as a partner organization due to both their willingness to provide data for further research and their heavy usage of social media when managing the response to a disaster situation. The Red Cross' response to the Fort McMurray wildfires is noteworthy as according to their internal documentation, it was the first disaster in Canada where the organization relied on social media and analytics.

This paper begins with a literature review examining previous research in this field and then discusses the research question at hand. With the question clarified, the paper moves on to discussing the data sources used and the model used to analyze them. This model's insights are examined alongside areas for future research in this field.

## Literature Review

Firstly, the objective of this literature review is to evaluate previous work done in the field about the usage of social media after a humanitarian crisis, especially among non-profit organizations. Five papers are examined, each looking at various contexts in which social media has been used after a humanitarian crisis.

Firstly, the research examines which factors affect information diffusion on social media after a disaster. Yoo et al. delve into the speed of information diffusion on social networks following a disaster within the context of 2012's Hurricane Sandy (123). Their research evaluates three propositions (Yoo et al. 125):

1. The higher the influence of a given user, the higher speed of diffusion of information when that user is the source.
2. If information increases situational awareness of a disaster, the speed of diffusion of information will be higher for that instance of information than if the information does not increase situational awareness.
3. If certain information is released later, as opposed to information released earlier in the progression of a disaster event, its speed of diffusion will be lower.

Yoo et al. empirically test these propositions using a Twitter dataset of tweets associated with Hurricane Sandy (123). This leads to the key findings that the speed of information dissemination depends on the influence of the user that the information originated from and that information released earlier in a disaster diffuses faster due to information saturation occurring among users over time (Yoo et al. 131).

Yoo et al.'s work establishes that user influence and the timing of information matter, but its shortfall is that it does not determine whether difference between user groups impact both social media usage and effectiveness post-disaster.

This shortfall is overcome by Kim and Hastak's examination of different user groups post-disaster using a Facebook dataset from the 2016 Louisiana Flooding, specifically the official Facebook page of the City of Baton Rouge. Similar to Yoo et al., the authors found that the majority of social media engagement was within the first two weeks following the disaster and then declined over time (Kim and Hastak 94). Kim and Hastak used social network analysis to examine different user groups. They found that individuals had a different role than institutional actors (both government agencies and NGOs). Individuals were found to have higher degree and eigenvector centralities, indicating that their role within the overall network was to disseminate information (Kim and Hastak 94). In contrast, institutions had a high betweenness centrality - with their role being their connection of disparate networks (Kim and Hastak 94). An important note is that individual engagement on Facebook was measured by Facebook "likes", comments and shares - none of which is directly equivalent to a Twitter retweet. This leads to questions about the equivalency between social network analysis on Facebook versus Twitter.

Despite questions about the choice of social network analyzed, Kim and Hastak's findings are still applicable. Kim and Hastak's findings are shared by Abedin and Babar, who examined Twitter data during the 2014 Australian Bush Fires. Abedin and Babar also found that institutions and individual actors have differing roles in a social network (729). Australian institutional organizations were shown to communicate more and have more trusted information, however individuals had more engagement and significantly influenced the dissemination of information (Abedin and Babar 734-735).

The key takeaway from the work of both Kim and Hastak and Abedin and Babar is that non-profit organizations must be mindful about the impact of their social media presence. These organizations are effective at communicating information to disparate groups but they are not the main drivers of information dissemination. Instead, the main driver behind information spreading on social media post-disaster is the actions of individual social media users. This leads to a question: who uses social media during a disaster? After all, the user composition impacts how information spreads and what groups are targeted by this information. Zou et al. examine this question through the lens of Twitter data from Hurricane Sandy.

The demographics of post-disaster Twitter use are one of three objectives of Zou et al.'s work. Zou et al. examined Twitter demographics relating to Hurricane Sandy in three phases of the disaster cycle: preparedness, response and recovery (1423). From this data, the majority of Twitter users discussing the hurricane were concentrated around the Northeastern United States, specifically the areas likely to be directly impacted by Hurricane Sandy (Zou et al. 1435-1436). These users' Twitter activity peaked in the preparedness phase as users sought information on the upcoming hurricane (Zou et al. 1436). Zou et al. also examined the socioeconomic breakdown of users discussing the hurricane, with these users tending to be from more well-off areas (1436). Interestingly, the social media activity of well-off users peaked during the response and recovery phases (Zou et al. 1436).

From Zou et al.'s results, it is shown that social media usage is unevenly distributed among the population. As a result, non-profit organizations must keep this into consideration when determining their social media strategies. However, what social media strategies that have been used in the past by non-profits after a humanitarian disaster and how effective have they been?

There is a lack of literature answering this question and directly examining the entirety of a non-profits' social media strategy. However, Yan and Pedrasa-Martinez look at one aspect of a social media strategy, specifically the social engagement between non-profits and social media users (2514). Yan and Pedrasa-Martinez measured social engagement using both Facebook and Google Trends data from Hurricane Sandy (2515). Their findings were that the biggest contribution that organizations could provide on social media would be providing users with actionable information about how to provide help post-disaster (Yan and Pedrasa-Martinez 2530-2531). Combining this conclusion with Zou et al's conclusion that most social media users are located near the disaster zone demonstrates an opportunity for non-profit organizations to leverage nearby users to help others post-disaster.

In short, the literature in this field covers different aspects of social media post-disaster regarding both non-profit organizations and social media in general. However, there is a lack of literature covering the entirety of a non-profits' social media strategy – providing an opportunity for research in this field.

## Research Question

The main question that this work attempts to answer is: how effective is the use of social media by non-profits post-disaster in encouraging stakeholders to take action?

This report focuses on social media impressions as a metric used to measure the impact of various social media postings. Future research is planned to change the dependent variable from social media impressions to an offline action, such as volunteering or aid acceptance to determine the effectiveness of social media.

## Data Description

The primary dataset examined by this work are the tweets from the Canadian Red Cross (@redcrosscanada) and the Red Cross Alberta (@RedCrossAB) Twitter accounts between May 3, 2016 and August 1, 2016. This time frame covers both the response and recovery periods of the 2016 Fort McMurray wildfires in Alberta. These two accounts were chosen because they were both the most active accounts during the wildfires and they have the most historical data regarding followers in comparison to other provincial Red Cross accounts.

The Canadian Red Cross tweets were provided by the Red Cross in a dataset which includes the content of the tweets, their posting date, the number of impressions of each tweet and how many favorites, retweets and replies that each tweet received.

In contrast, the tweets from the Red Cross Alberta account were manually scraped off Twitter. Similarly to the Red Cross dataset, this dataset includes the content of tweets, their posting date and the number of favorites, retweets and replies per tweet. However, this dataset lacks data on the number of impressions of each tweet.

The Canadian Red Cross tweet dataset is 1,046 tweets and the Red Cross Alberta dataset has 690 tweets.

The primary dataset is supplemented by additional datasets. Firstly, the number of Twitter followers at the time of a tweet is used as a proxy for the number of impressions of tweets from the Red Cross Alberta account. Twitter does not keep historical follower data, so this data was accessed for various dates in 2016 that were archived in the Wayback Machine – a digital archive of the World Wide Web. The archived data is mostly focused on the first two weeks of May 2016 (when the wildfires were at their peak), with sporadic archiving in the remainder of the timeframe examined. As such, the missing data points were calculated using linear interpolation, with one value per day representing the number of followers for that day. An assumption is made that the number of followers would not significantly vary in a day, especially as the disaster moved well into its recovery period. This assumption is based on the finding of Kim and Hastak that social media engagement peaks within the first two weeks post-disaster (94). As a result, the majority of relevant trends in social media engagement is captured by the archived data.

Another supplementary dataset used is the Google Trends index for the organization under scrutiny, whether it was the Canadian Red Cross or the Alberta Red Cross. The purpose of this dataset in the analysis is to account for general trends in interest which may affect engagement with the Red Cross' social media. This dataset was collected directly from the Google Trends website, with relative interest for search terms broken down on a daily basis.

## Model

The model used in this work is a logistic regression model measuring the impact on the social media engagement of a tweet from the tweet's content and the cumulative characteristics of the organization's Twitter page within a recent time period. For some iterations of the model, a third independent variable – the daily Google Trends index for the chosen organization was added.

The dependent variable of social media engagement is measured by a ratio of the retweets per tweet to the impressions per tweet. Tweets with a higher ratio manage to better engage viewers and the converse holds for tweets with a lower ratio. The data used to calculate this variable is based on the existing dataset provided by the Canadian Red Cross. For the Alberta account, the dependent variable is slightly altered to be a ratio of retweets to the number of followers at the time of the tweet. The number of followers is not an exact proxy to the number of impressions, but it should reflect similar results – namely tweets which have a higher ratio engaged a larger proportion of viewers than tweets with a lower ratio.

The first independent variable is the content of the tweet itself. To quantify a tweet's content, two categories were identified for a tweet to fall within – actionable and non-actionable tweets. An actionable tweet is one which clearly implores viewers to take an action. These actions could potentially be quantified by the Red Cross. Examples of actions included donations, volunteer opportunities, aid collection and general social media engagement (e.g. a contest). On the other hand, non-actionable tweets have a more informative nature, with a focus on promoting positive stories from the disaster zone.

A separate, scraped dataset of 1,019 tweets from both the national Red Cross Twitter account and 10 regional ones in May-August 2016 were manually classified as being either actionable or non-actionable. After manual classification, these tweets were processed and cleaned. The cleaning began with case-folding tweets and ensuring that all tokens processed were in lowercase. In the next step, punctuation was stripped from the dataset. One specific challenge that had to be handled was dealing with the constraints of Twitter. An example of a constraint was standardizing links to both other tweets and to external websites alongside links to other forms of media. This standardization involved replacing all unique links with a general phrase indicating the type of link that was replaced. Another constraint was handling the punctuation types @ and #, which have specific meanings on Twitter and cannot be stripped like other punctuation. As such, these symbols were also replaced with a general phrase indicating the punctuation that had been replaced. The specifics of this replacement are found in Appendix 1. Afterwards, the tweets were broken down into individual tokens which were tagged with their part-of-speech using Python's NLTK package. From these tokens, stopwords were removed and the remaining tokens were lemmatized to ensure consistency between different forms of the same word. The processed tokens were then rejoined to create a fully processed version of the original tweet.

The separate dataset was used to train a Bernoulli Naïve Bayes classifier in Python. The Bernoulli classifier was chosen because of its effectiveness in classifying binary features, such as the actionable versus non-actionable choice in this dataset. Before applying the classifier, the tweets were vectorized into a matrix of TF-IDF features. The Naïve Bayes classifier was trained on these vectorized tweets alongside the binary decision of actionable versus non-actionable.

The same preprocessing procedures were performed on the combined dataset of Canadian Red Cross and Alberta Red Cross tweets. Afterwards, the trained model was applied to the combined dataset, where it classified each tweet and provided the probability that a tweet was actionable. This probability is used as a quantitative metrics of a tweet's content in the overall regression.

The second independent variable is the cumulative characteristics of the organization's Twitter page within a given time frame – either a day or a week. The purpose of this variable is to attempt to account for carry-over effects between multiple tweets in a time period – where one tweet's popularity leads to subsequent tweets being more popular than they would have otherwise been. The cumulative sum of these characteristics reset to 0 at the end of each time period. Due to the dynamic nature of a disaster, these carry-over effects are measured for both each day within the dataset's time period and each week within this period. The two time periods are used in different regressions to determine whether daily or weekly carry-over effects have a more significant impact on the engagement of a tweet.

The specific characteristics that are measured cumulatively were retweets, favorites and replies. Each characteristic is treated as a separate independent variable, with each regression only using one cumulative characteristic. The choice of only using one characteristic in a regression is to avoid multicollinearity as an assumption was made that retweets, favorites and replies are correlated with each other. As such, multiple regressions are run with different cumulative characteristic – to determine if any characteristic holds more of an impact over a tweet's engagement than another.

The final independent variable used is the daily Google Trend index for a chosen organization. This variable is used to determine if general interest trends significantly impact a tweet's social media engagement. This variable is only added to some iterations of the model to determine if external trends have a significant influence on social media engagement or if these trends can be accounted for in the cumulative characteristics of an organization's account.

The specific model used is a logistic regression model as the dependent variable's values always fall between 0 and 1 and the relationship between the dependent and independent variables is a non-linear one. This logistic regression model follows a quasi-binomial distribution to account for variance in the data which would not be accounted for within a binomial distribution.

The general model has the following equation:

$$log(Engagement\ Rate) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3$$

In this equation, $x_1$ refers to the tweet's content, $x_2$ to the cumulative characteristic and $x_3$ to the Google Trend value (for the regressions where this variable is included).

## Findings

24 iterations of the regression equation were run – 12 for both the Canadian Red Cross and the Alberta Red Cross. Within these twelve regressions, 6 each were run with Google Trends data and 6 without this data. These 6 regressions include 3 with weekly cumulative characteristics and 3 with daily one. For each time period, the three regressions have different characteristics – namely retweets, replies and favorites. This section delves into detail for all twelve regressions run for the Canadian Red Cross account and then compares selected results with the regressions of the Alberta Red Cross.

The first regressions examined in detail are those for the Canadian Red Cross. The initial point of examination are the differences between weekly cumulative characteristics and daily cumulative characteristics, excluding Google Trends data. These results are shown in Figure 1.

**Fig. 1: Comparing daily and weekly cumulative characteristics without Google Trends data**

| Regression | Variables | Estimate | Standard Error | T-value |
|---|---|---|---|---|
| Daily Cumulative Retweets | Constant | -6.122 *** | $3.832*10^{-2}$ | -159.754 |
| | Content | 0.1857 | 0.1191 | 1.559 |
| | Cumulative Retweet Sum | $-1.875 * 10^{-4}$ *** | $2.973 * 10^{-5}$ | -6.307 |
| Weekly Cumulative Retweets | Constant | -5.907 *** | $3.804*10^{-2}$ | -155.28 |
| | Content | 0.2285 * | 0.1075 | 2.127 |
| | Cumulative Retweet Sum | $-8.387 * 10^{-5}$ *** | $6.644 * 10^{-6}$ | -12.624 |
| Daily Cumulative Favorites | Constant | -8.307 *** | 0.442 | -18.804 |
| | Content | 1.786 *** | 0.461 | 3.876 |
| | Cumulative Favorite Sum | 0.004 *** | 0.001 | 4.503 |
| Weekly Cumulative Favorites | Constant | -7.535 *** | 0.437 | -17.244 |
| | Content | 1.575 ** | 0.572 | 2.753 |
| | Cumulative Favorite Sum | 0.0003 | 0.0003 | 0.981 |
| Daily Cumulative Replies | Constant | -7.959 *** | 0.568 | -14.007 |
| | Content | 1.746 ** | 0.592 | 2.950 |
| | Cumulative Replies Sum | 0.028 | 0.015 | 1.911 |
| Weekly Cumulative Replies | Constant | -7.191 *** | 0.435 | -16.544 |
| | Content | 1.786 *** | 0.529 | 3.377 |
| | Cumulative Replies Sum | -0.002 | 0.004 | -0.459 |

Note: *, ** and *** indicate significance at the 95%, 99% and 99.9% levels, respectively.

Looking at Figure 1, the three cumulative characteristics display differing results. Firstly, the two regressions comparing retweets show that cumulative retweets have a high impact on social engagement. This impact is shown by the low p-values of these estimates. This high significance level (99%) is most likely because the a portion of dependent variable is based on retweets. As a result, the more important relationships to highlight are those involving cumulative favorites and replies. Among these remaining regressions, the results are similar – the content is highly significant while the cumulative amounts for both favorites and replies are non-significant. One exception is the daily cumulative favorites, which is shown to be highly significant. This significance is supported by a t-value of 4.503, which suggests that there are carry-over effects between the favorites of the tweets from the same day. However, as neither the daily cumulative replies sum nor the weekly cumulative favorites sum is shown to be significant, it is unclear whether this significance can be attribute to the time period or the characteristic in question. A potential source of this significance could be the daily cumulative replies sum due to its t-value of 1.911 – which is near the "rule of thumb" value of $t = 2$, where t would be considered statistically significant at the 95% level. As such, these cumulative characteristics are fully examined with Google Trends data - as shown by Figure 2.

**Fig. 2: Comparing daily and weekly cumulative characteristics with Google Trends data**

| Regression | Variables | Estimate | Standard Error | T-value |
|---|---|---|---|---|
| **Daily Cumulative Retweets** | **Constant** | -5.869 *** | $3.940 * 10^{-2}$ | -148.954 |
| | **Content** | 0.198 | 0.107 | 1.847 |
| | **Cumulative Retweet Sum** | $-1.220 * 10^{-4}$ *** | $2.296 * 10^{-5}$ | -5.313 |
| | **Google Trend Value** | $-1.453 * 10^{-2}$ *** | $1.450 * 10^{-3}$ | -10.021 |
| **Weekly Cumulative Retweets** | **Constant** | -5.873 *** | $3.907 * 10^{-2}$ | -150.316 |
| | **Content** | 0.222 * | 0.107 | 2.079 |
| | **Cumulative Retweet Sum** | $-5.554*10^{-5}$ *** | $1.024 * 10^{-5}$ | -5.423 |
| | **Google Trend Value** | $-7.260*10^{-3}$ *** | $2.143 * 10^{-3}$ | -3.388 |
| **Daily Cumulative Favorites** | **Constant** | -5.869 *** | $3.963 * 10^{-2}$ | -148.085 |
| | **Content** | 0.197 | 0.107 | 1.836 |
| | **Cumulative Favorite Sum** | $-9.043 * 10^{-5}$ *** | $1.947 * 10^{-5}$ | -4.644 |
| | **Google Trend Value** | $1.541 * 10^{-2}$ *** | $1.455 * 10^{-3}$ | -10.592 |
| **Weekly Cumulative Favorites** | **Constant** | -5.822 *** | $3.873 * 10^{-2}$ | -150.310 |
| | **Content** | 0.230 * | 0.105 | 2.195 |
| | **Cumulative Favorite Sum** | $-5.918 * 10^{-5}$ *** | $8.261 * 10^{-6}$ | -7.165 |
| | **Google Trend Value** | $-1.074 * 10^{-2}$ **** | $1.582 * 10^{-3}$ | -6.787 |
| **Daily Cumulative Replies** | **Constant** | -5.865 *** | 0.039 | -148.898 |
| | **Content** | 0.203 | 0.107 | 1.902 |
| | **Cumulative Replies Sum** | -0.006 *** | 0.001 | -5.364 |
| | **Google Trend Value** | -0.013 *** | 0.001 | -8.891 |
| **Weekly Cumulative Replies** | **Constant** | -5.871 *** | 0.040 | -148.102 |
| | **Content** | 0.225 * | 0.107 | 2.091 |
| | **Cumulative Replies Sum** | -0.002 *** | 0.0003 | -4.594 |
| | **Google Trend Value** | -0.009 *** | 0.002 | -4.401 |

Note: *, ** and *** indicate significance at the 95%, 99% and 99.9% levels, respectively.

From Figure 2, the addition of the Google Trends data changes all the regressions, regardless of time period or cumulative characteristic used. In each of the regressions, the Google Trend variable is considered significant at the 99.9% level – which indicates that when a topic is being widely searched for (hence a high Google Trend value), it leads to more engagement with the Red Cross' social media posts. As a result, the Google Trends data acts as a control variable to account for the excess engagement and popularity. Another similarity across the regressions is the estimate and significance for the constant term and the content variable. For the constant term, regardless of the cumulative characteristic or time period in question – it has an estimate around -5.87 that is significant at the 99.9% level, similar standard errors and similar T-values. Moving to the content variable, it is statistically significant at the 95% level for the weekly time period, but not the daily ones. However, for the daily time period, the t-values between 1.8 and 1.9 indicate that the content is still relatively important when considering tweets on a daily level. As such, the daily time period cannot be discarded, with the report focusing solely on analyzing at a weekly level. Finally, for the cumulative summations, all three characteristics are highly significant at the 99.9% level, regardless of time period.

One concern that is raised from including the Google Trends data is whether it is multicollinear with the cumulative characteristic values. The cause of this concern is because adding the Google Trends data to the regressions causes all the cumulative characteristic variables to be considered highly significant – which was not the case for when the Google Trends data was excluded. To determine if multicollinearity exists, the Variance Inflation Factors (VIF) of the regressions have been calculated. These VIFs are shown in Figure 3.

**Figure 3: VIF for each regression with Google Trends data**

| | **VIF Values** | | |
|---|---|---|---|
| | **Content** | **Cumulative Characteristic Sum** | **Google Trend Value** |
| **Daily Cumulative Retweets** | 1.000 | 1.049 | 1.049 |
| **Weekly Cumulative Retweets** | 1.001 | 2.404 | 2.403 |
| **Daily Cumulative Favorites** | 1.000 | 1.028 | 1.028 |
| **Weekly Cumulative Favorites** | 1.000 | 1.361 | 1.360 |
| **Daily Cumulative Replies** | 1.000 | 1.133 | 1.133 |
| **Weekly Cumulative Replies** | 1.001 | 2.198 | 2.196 |

From the VIFs in Figure 3, all the VIFs are between 1 and 2.41. This indicates a slight correlation between the cumulative characteristic variables and the Google Trend values. The higher VIFs are for the weekly time period, which indicates that Google Trend and cumulative characteristics aggregated over a week are more likely to be correlated together than when broken up over a daily period. However, the VIF values are low enough to not be of concern, so multicollinearity does not significantly affect the insights obtained from this model.

Altogether, the insights from this analysis into the Canadian Red Cross account are that the content of a tweet does not have much of an impact on the engagement of a social media post. Instead, the main factor which influences the engagement of a tweet is the cumulative characteristics which measure the carry-over effects between multiple tweets.  The time period over which cumulative characteristics are measured does not make much of a difference on the influence of carry-over effects on a post's engagement. These insights are found when controlling for overall trends using Google Trends data.

The next set of regressions that is examined is about the Alberta Red Cross' Twitter posts to determine if they lead to similar findings as the analysis of the Canadian Red Cross' posts. As the final insights from the Canadian Red Cross' analysis were conducted with Google Trends data as a control variable, Figure 4 compares the daily and weekly characteristics with this Google Trends data.

**Fig. 4: Comparing daily and weekly cumulative characteristics with Google Trends data**

| Regression | Variables | Estimate | Standard Error | T-value |
|---|---|---|---|---|
| **Daily Cumulative Retweets** | **Constant** | -8.882 *** | 0.621 | -14.311 |
| | **Content** | 1.788 *** | 0.423 | 4.223 |
| | **Cumulative Retweet Sum** | 0.001 *** | 0.0003 | 4.255 |
| | **Google Trend Value** | 0.014 * | 0.008 | 1.964 |
| **Weekly Cumulative Retweets** | **Constant** | -8.312 *** | 0.571 | -14.553 |
| | **Content** | 1.764 *** | 0.507 | 3.480 |
| | **Cumulative Retweet Sum** | $-1.874 * 10^{-5}$ | $2.304 * 10^{-4}$ | -0.081 |
| | **Google Trend Value** | $1.868 * 10^{-2}$ * | $9.256 * 10^{-3}$ | 2.019 |
| **Daily Cumulative Favorites** | **Constant** | -8.722 *** | 0.625 | -13.954 |
| | **Content** | 1.797 *** | 0.456 | 3.937 |
| | **Cumulative Favorite Sum** | 0.004 *** | 0.001 | 3.682 |
| | **Google Trend Value** | 0.009 | 0.008 | 1.087 |
| **Weekly Cumulative Favorites** | **Constant** | -8.300 *** | 0.563 | -14.753 |
| | **Content** | 1.790 *** | 0.499 | 3.586 |
| | **Cumulative Favorite Sum** | -0.0001 | 0.0004 | -0.273 |
| | **Google Trend Value** | 0.019 * | 0.008 | 2.310 |
| **Daily Cumulative Replies** | **Constant** | -8.514 *** | 0.683 | -12.469 |
| | **Content** | 1.772 ** | 0.539 | 3.285 |
| | **Cumulative Replies Sum** | 0.017 | 0.016 | 1.060 |
| | **Google Trend Value** | 0.015 | 0.009 | 1.664 |
| **Weekly Cumulative Replies** | **Constant** | -8.043 *** | 0.484 | -16.632 |
| | **Content** | 1.931 *** | 0.414 | 4.658 |
| | **Cumulative Replies Sum** | -0.008 | 0.005 | -1.811 |
| | **Google Trend Value** | 0.024 *** | 0.007 | 3.405 |

Note: *, ** and *** indicate significance at the 95%, 99% and 99.9% levels, respectively.

Figure 4 indicates that the content of a tweet is statistically significant, regardless of the cumulative characteristic or time period used. At the same time, the cumulative characteristic variable is only significant for daily retweets and daily favorites. Also, the Google Trend value is only significant at the 99.9% level for the weekly cumulative replies level while it is significant at the 95% level for weekly cumulative favorites and both daily and weekly cumulative replies.

The main insight from Figure 4 is that the most important factor affecting the engagement of a tweet is its content. At the same time, carry-over effects do not significantly impact engagement on a weekly level. On a daily level, carry-over effects impact engagement when the characteristic measured is retweets or favorites, but not replies. Finally, the control variable of the Google Trends index is shown to have a significant impact only in certain situations.

The insights derived from the Alberta Red Cross dataset are quite different from those from the Canadian Red Cross dataset. The Alberta Red Cross findings state that a tweet's content is the most influential factor in social media engagement while the Canadian Red Cross findings show the most influential factor is carry-over effects of previous postings. Delving further into carry-over effects, the Canadian Red Cross account does not show a significant difference between daily and weekly carry-over effects, while the Alberta Red Cross account analysis highlights daily carry-over effects as being more impactful than weekly carry-over effects.

A potential reason behind these differences could be the differences in the metric used to measure engagement, with the Canadian Red Cross analysis using the ratio of retweets to impressions and the Alberta Red Cross analysis using the ratio of retweets to followers. To verify these results, impression data needs to be acquired for the Alberta Red Cross' postings.

Another factor causing the differing results between the Canadian and Alberta Red Cross accounts could be due to the relatively small samples of data (1,736 tweets) being analyzed. A potential method to resolve this would be to obtain a larger dataset of tweets. This dataset could consist of tweets by these accounts from other disasters or analyzing the tweets of other non-profit organizations during the Fort McMurray wildfires. One concern raised by this potential solution is that adding additional disasters or organization could impact the data quality and raise concerns about the overall findings of this analysis.

## Conclusions and Areas for Future Study

This work attempts to determine the determinants which impact the engagement of social media postings of a non-profit organization post-disaster. This work examines the Canadian Red Cross and the Alberta Red Cross' tweets during the 2016 Fort McMurray Wildfires. The two organization's accounts show contrasting results – the most significant factor impacting engagement for the Canadian Red Cross are carry-over effects between multiple postings within a similar time frame. In contrast, the most significant factors for the Alberta Red Cross are the contents of the tweets themselves. The differing results can be potentially attributed to differences in the dependent variable being measured or due to the size of the dataset being used.

These results demonstrate that there is a significant amount of opportunity for future study in this field. Planned areas for future study would be to expand the question further and examine the entirety of a non-profit organization's social media strategy. This expansion can be broken down into two overarching sections: analyzing the social media strategy itself in further depth and examining the offline effects created by this social media strategy. Further analysis of the social media strategy will be conducted using social network analysis to map information dissemination and identify the Red Cross' role in the overall network of social media post-wildfire.

Also, the offline effects of the Red Cross' social media strategy can be measured through their impact on fundraising, volunteering and acceptance of aid. With these offline effects as the dependent variable, the above analyses can be rerun to determine whether overall trends or the actual content of social media posts have an impact on offline effects.

Depending on the availability of data, these areas will be examined through statistical analysis to determine what, if any, impact the Red Cross' social media strategy has on these offline factors.

## Appendices

**Appendix 1 : Link and Selected Punctuation Replacement during Tweet Cleaning**

| Initial Text Type | Replacement Phrase | Reasoning |
|---|---|---|
| Link to another Tweet | TWITTERLINK | Used to link to other tweets referenced by the initial tweet |
| Link to external website | WEBLINK | Used to link to external websites, especially that of the Red Cross |
| Link to external media (e.g. photos or videos) | TWITTERPIC | Used to enhance tweets with various photographs and/or videos |
| @ | ATSIGN | Used by Twitter to indicate another account |
| # | HASHTAG | Used to reflect a trending topic on Twitter |

**Appendix 2: Link to R Code for Regressions**

The code behind the regressions can be found at https://github.com/aleemdamji/BUSA400-Code/blob/master/finalLogitRegression.R

## References

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