Impact of Emotions in Social Media Content Diffusion

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Emotions present in social media content shape its diffusion. This study seeks to comprehensively examine the impact created by emotions of a social media message on its diffusion. Centered on a non-domain specific Twitter dataset, the authors define several measurement constructs to quantify the tweet diffusion process namely, speed, size, half-life, diffusion potential, and engagement. Since a message may express a single dominant emotion or multiple categories of emotions, the current study focuses to investigate the influence of emotions in the single label as well as multi-label setting. Through extensive statistical analyses (Multivariate Analysis of Variance and Regression), we find that the impact of emotions on diffusion constructs was statistically significant. The findings shed light on how emotions aid or hinder the spread of information through social media. Specifically, the tweets containing joy or contempt as primary emotion attained faster and stronger diffusion. In contrast, anger or fear as primary emotion in tweets contributed to slower and weaker diffusion. Also, the combination of one or more positive and negative emotions increased the diffusion outcome.

Povzetek: Analiziran je vpliv pozitivnih in negativnih čustev na hitrost razširjanje čivka oz. tvita.

1   Introduction

With the advent of technology, the world has moved online and so has the interactions. Every day, social media platforms cater to a huge number of interactions- approx. 900 million photos on Facebook, 500 million tweets, and 0.4 million hours of YouTube videos[1]. These digital interactions have led to the generation of data at an unprecedented rate. In this digital climate, social media has become a major component of the very existence of our lives. Social media communications are a reflection of the real world and hence emotions are an integral element of the content so produced. People not only share their memories, personal stories, achievements, and failures but also their reactions to socio-political developments around them, reviews, and reactions to a product or service they used. Thus, the data not only reflects the writer's state of mind but also affects readers and hence influences decision making in various aspects [1] [2].

As social media channels serve as interaction tools, they have functioned as major facilitators of public expression. Social media sites including Twitter, Facebook, and Reddit, have facilitated easy information sharing and large-scale information cascades. The impact of these digital interactions is quite instrumental on our society and industry. One of the most intriguing aspects of these digital interactions is how they spread. Understanding the process of diffusion of information over social media platforms could assist the development of a safer environment for users, prevent fake news, and support business growth.

Whenever users come across a piece of content they usually interact with liking, commenting, or sharing the piece within their network. However, the virality or reach of content is described by the "sharing" phenomenon. Sharing content is quite fascinating and usually requires a strong connection with the reader to make him or her share it with their network. Typically, people share something on social media when something strikes a chord with them, be it political, emotional, sexy, or funny. People like to reflect their perception of the world with others, as well as their tastes and self-identification.

Emotionally charged content transmits rapidly and shapes our thoughts and actions. In the case of mass movements, socio-political upheaval, disasters, and terrorism, these media platforms allow an expeditious propagation facilitated by the strong emotional nature of the content. This virality assists preparedness and a much better-informed reaction to the situation. Likewise, in case of hate speech, derogatory content, or false information, the embedded emotions may facilitate a quick peer-to-peer spreading leading to rather harmful results. Thus, the emotionally charged content we read and share across social media platforms shape our views and notion of society, politics, ideology, and morality as well.

Notably, social media platforms influence the readers of their content. For example, our purchasing decision after reading the customer reviews about a product. Nowadays, these interactions have become a part of social media landscapes. People express their pleasure, displeasure towards the government, society, ideology, or personal

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[1] https://www.whishworks.com/blog/data-analytics/
understanding-the-3-vs-of-big-data-volume-velocity-and-variety/

state. These expressions once shared and spread influence the people in establishing their views, opinions and sometimes lead to strong actions or reactions. The link between what is shared and how it spreads is crucial to explore, understand, guide, and control the impact which may be either positive or negative.

Social media and its interesting sharing capabilities have piqued the interest of the research fraternity to study and analyze both the emotional element of content being produced and what makes it spread. The research would assist the development of intelligence that could help us, decode the ties between the digital and real-world, its interactions, and how it affects socio-political and commercial applications. It will also assist in improving the mental and emotional well-being of the individuals.

A lot of studies have been done in this direction and researchers have theorized and evaluated various models to understand the diffusion behavior of social media platforms. Forgas [3] proposed that emotions tend to impact what we notice, what we understand, what we recall, and eventually what sorts of decisions and choices we make. Emotions in social media content are proposed as a significant factor that may impact the mechanism of diffusion [4], [5]. The findings of past social media research suggest that the emotional valence of online content (positive, negative, or both) could cause a higher degree of cognitive involvement and enthusiasm, which can, in turn, impact the exchange of information [6]. Also, it may be noted that, apart from the polarity of the content, certain other factors affect the spread of emotional information. In addition to valence, emotions differ on the degree of physiological arousal they elicit [7]. The current study, therefore, goes beyond emotional polarity and delves deeper to explore how distinct emotions influence the diffusion of information.

Moreover, prior research which examines the impact of emotions embedded in online content on its diffusion is primarily driven by a single emotion model. While psychologists have researched emotions for a long time, there exists no universal agreement on a single standard set of basic emotions. As a result, the participants in this study consented to use four alternative models of emotion classification that are widely used by computer linguistics and natural language processing (NLP) researchers. By analyzing facial expressions, Paul Ekman identified six basic emotions[8]. Robert Plutchik [9] came up with an extension to the Ekman model by adding two more emotion categories and introduced its categorization in a wheel of emotions. Another popular emotion model was proposed by Parrott[10] in the form of a tree-structured list containing emotions in the primary, secondary and tertiary levels where the primary level is composed of six emotion categories (love, joy, surprise, anger, sadness, and fear). None of the above-mentioned models included significant social emotions i.e. shame and guilt hence we choose to include yet another widely-used model in emotion detection literature i.e. Izard ten emotion model [11].

Also, given the real nature of textual content where a single piece of text is usually associated with multiple emotion labels, it becomes empirically challenging to capture the multi-label aspect of emotion classification

while analyzing the mechanism of diffusion. To this end, the scant literature gives authors another motivation to study the influence of joint multiple emotions carried by a single piece of content on its diffusion mechanism. In light of these debates and research gaps, we find an opportunity to advance prior research by examining the role of specific emotion categories in the social media content diffusion process.

This paper contributes to the broader literature on information propagation by:

1. Framing a set of emotions based on five well-accepted emotion classifications;
2. Proposing a multi-dimensional measure for social media information diffusion, including size, speed, engagement, half-life, and diffusion potential.
3. Investigating the impact of single or multiple emotions present in a tweet on its diffusion;
4. Statistically analyzing which emotions emerge to be most significant in the propagation of information.

The next section builds the background by presenting a discussion on the related literature on the impact of emotions on content diffusion. Section 3 is divided into four subsections. The first subsection proposes a set of emotions based on four emotion classification models. The second subsection outlines the data collection methodology followed by a list of measurement constructs used in the analyses. The last subsection reports the methods used in statistical analysis. Finally, the results of the proposed analysis are reported in section 4. Section 5 presents a discussion on findings and the limitations of the current study. The conclusions of this study are reported in Section 6.

2 Related background

Information diffusion is an active research domain attracting the eyes of researchers from social, physical, and computational sciences. Furthermore, information dissemination in terms of online word-of-mouth and viral marketing has been discussed in the business and marketing literature (e.g., [12][13][14]).

2.1 Emotions and information diffusion

One of the major critical questions in understanding the nature of information diffusion and explore its applications is to analyze the drivers of the phenomenon [15][16][17][18][19]. Notably, emotions are found to be one of the powerful predictors in online content dissemination. People communicate by emotionally charged messages over social media to strengthen their social connections, build persona [6], and rationalize their emotional experiences [20]. The emotions ingrained in the content, in turn, impact the interaction with the content/social media messages making it diffuse. It also affects the emotional states of readers and their ensuing decisions [21][22][20][23].

Broadly categorizing emotions into two buckets-positive and negative, the research fraternity is divide into

whether positive emotions or negative emotions possess a stronger and wider reach. One group of research community suggests that negative emotions, i.e. posts having negativity bias are more likely to collect greater responses and be exchanged faster on social media networks [5]. Scholars have also observed higher negative content while researching for information diffusion, implying negative posts are exchanged more and receive more responses [24]. However, the other group of researchers has reflected that positive posts on social media are in higher quantity than negative ones creating a positivity bias [25][26]. In this way, the research fraternity had been continuously wrangling between positivity bias and negativity bias on emotions in social media.

Ferrara & Yang [27] studied the nature of the adoption of positive and negative content on Twitter. They studied 3,800 Twitter users for a week and assessed the valence of information exposed to users before publishing their tweets. They observed that positive posts follow an over-exposure of 4.5 percent above average when compared to negative posts which occur after overexposure of 4.34 percent above average. They concluded that positive content has a higher probability of adoption among Twitter users. In another study [28], the authors studied 19,766,112 English tweets. They discovered that positive tweets are proffered more, over negative and neutral tweets, being favored over 5 times. Also, the positive tweets garnered a higher sum of retweets. The sum of retweets on positive posts was approx. 2.5 times more than the sum of tweets collected over neutral and negative tweets. The study on newsgroup participation by Joyce and kraut [29] acclaimed that positive emotions obtain a larger set of comments and easily shared, respectively.

While a good number of researchers have advocated positivity bias in diffusion, others suggested negativity bias be a stronger phenomenon [24][5]. Positive and negative stimuli elicit very distinct responses, according to research in psychology and organizational studies. Negative emotions induce higher and stronger responses pertaining to behavioral and cognitive stimuli when compared with the response generated over positive emotions [30][31][32]. Past studies have advocated negativity bias, which has been extended by [33]. He analyzed negative emotional responses generated by twitter news and commented that negative news generates strong negative emotions amongst the readers [33]. Stieglitz and Dang-Xuan [5] also approved the presence of negativity bias in social media. He studied the diffusion impact of emotions and observed that negative emotions generate more responses and retweets than positive ones.

Against this backdrop, it is clear that there are conflicting results on the role of emotions in content diffusion and that the discourse on positivity bias or negative bias never ends. However, there is a strong consensus among scholars that emotions have a significant impact on the exchange of information. Pfitzner et al. [34] studied the effect of emotions in the distribution of messages on Twitter. He discovered that emotionally charged messages, i.e. messages having positive or negative emotions spread faster and more when compared with neutral messages. The emotionally charged messages

have a five times higher probability of being retweeted [35]. Hill et al. [36] proved that emotional divergence accelerates distribution and hence dissemination of information. Based on the studies, it can be inferred that expressions of emotions on social media, will attract more attention and arousal, leading to accelerated diffusion and sharing on social media.

However, we observed a research gap underlying the vast depth of work done to analyze the drivers of information diffusion. Despite significant research contributions on the impact of emotions on information diffusion, the majority of them only study the effect of sentiment (valence) on the diffusion of online content [37][28]. In these studies, valence was defined as a unidimensional construct that measured the total volume of emotion in a message. Lately, increasing attention has been paid by the research community to the role of specific emotion categories as defined by some of the popular emotion models [38][39]. These specific categories of emotions include fear, joy, anger, guilt, and sadness, etc. Also, most experiments on the impact of emotions on social media information diffusion had been domain-specific making it yet more difficult to generalize the effects of emotions on the diffusion of social media content.

In a more recent study, Brady et al. [40] studied negative emotions on topics- gun control & climate change, on Twitter. He discovered that the diffusion of these messages was positively related to negative emotions. His similar study on same-sex lifestyles showed that diffusion likelihood was negatively related to similar kinds of emotions. The research work concluded that the context or subject of the messages also affects the process of diffusion. In another study on Instagram, on engagement in the context of melanoma, Cho et al. [32] discovered that expressions of anger generated more interaction in terms of "likes", while expressions of fear and joy elicit less engagement. Paek et al. [41] found that messages that evoke fear as an emotion, elicit more engagement. Myrick et al. [42] discovered that sadness, anger & fear diffuse with negativity bias in tweets with the #stupidcancer hashtag. Another research by Wang & Wei [43] concluded that anger is positively correlated to information diffusion for cancer-related discussions. Very recent research by Wang and Lee [44] also analyzed the impact of negative emotions on cancer tweet diffusion. Meanwhile, other studies have discovered that negative emotions do not widely circulate general knowledge [25], political [5], or health-related signals [39]. Wang et al. [45] analyzed the role of fear and hope emotion on cancer diffusion.

Hence, the research on the role of specific positive and negative emotion categories on information diffusion still stays in an embryonic stage which provides strong theoretical support for the current study. Additionally, emotions are quite complex and interrelated in reality. A situation could generate multiple emotions that could reflect in the messages posted on social media platforms. For example, a bad event could lead an individual to experience sadness, disgust, and anger at the same time and this experience reflects well in the posts shared by

them. Hence, classifying a piece of social media text into a single emotion category is inconsistent with reality as it may be associated with multiple emotion categories. This multi-label aspect of emotions is well-recognized in emotion classification literature. However, it is still understudied, particularly in terms of how multiple emotions present in a tweet may jointly contribute to the diffusion of social media content.

2.2   The complex nature of information diffusion

Individual social media users exchange information through simple activities, like retweeting, posting on Facebook, or email forwarding, but the information diffusion process is complicated and dynamic [46]. Studies exploring the process of information diffusion on social media have been vaguely described and measured generally while missing out on the multi-dimensional nature of the process. While several dimensions exist to conceptualize and operationalize the features of online diffusion, most studies have been centered on the size of diffusion, but the rate at which knowledge disseminates over time has largely been overlooked.

Size of diffusion which measures the total number of retweets received by a tweet is an important factor, however, it measures the static nature of the process only and misses out on quite crucial components like the speed of diffusion[47]. Lately, a growing number of researchers have started focusing upon the dynamic components of diffusion, i.e. the temporal dynamics of information, particularly the speed with which the information diffusion occurs on the social media platforms[5][48][49]. Taking motivation from the exploratory reading process of these studies, we centralize our research on both of these important dimensions of information diffusion i.e. size and speed.

Speed has been conceptualized in two different ways in the theory of innovation diffusion[50]. First, speed refers to the amount of time taken during the innovation-decision process by which "an individual passes from first knowledge of an innovation to forming an attitude toward the innovation, to a decision to adopt or reject" the new idea. Similarly, in case of social media content diffusion, sharing actions such as retweeting, suggests that a person is interested to absorb the information [51]. Hence, the theory of innovation diffusion can be used here. So, the time interval between a piece of information was exposed to sharing, signals the speed by which individual transitions from acknowledging to adopting the information. The lesser the time between the two events, the faster the information diffuses. The time interval was utilized as a proxy for speed in most research on information diffusion [5][52][48][53][49]. For example, Zhang and Peng [49] discovered that the first diffusion of advertising messages on microblogging sites might take anywhere from 1 hour to 3650 hours. The rate of adoption is another useful indicator for determining diffusion speed. The number of people who adopted the idea in a specified time period is known as the rate of adoption. This metric was first used by Zhu et al. [52] to examine

the effect of message characteristics on information diffusion. They worked on the official CDC Twitter account and tracked the diffusion of health-related messages for six days following its publication. The time interval between exposure of a message to its adoption depicts how long it takes for a message to get its first diffusion. On the other hand, the rate of diffusion, i.e. number of adoptions in a specific interval of time, gives a hint of how many people were compelled to share it over a while. A message may receive the first retweet quite early and still miss out on large sharing numbers and similarly, a message could get a good number of retweets but still have a long wait for its kickstart. The current study evaluates speed by distinguishing between the time interval and the rate of adoption in order to gain a comprehensive and deeper knowledge of information diffusion and how quickly it travels throughout the realms of social media. To date, no research has taken into account the impact of emotions on the rate of adoption, particularly in the social media context.

3   Data and proposed methodology

First, this section discusses the four widely adopted emotion classification models. After continuous research for decades, there exists no agreement between psychologists on a universal set of basic emotions. This motivates us to frame a set of emotions by unifying the popular emotion models. In the continuing subsection, the data collection process and experimental settings have been presented. Further subsection introduced the proposed measures of information diffusion.

3.1   Emotion classifications

Ekman [8] proposed a set of six elemental emotions - sadness, fear, disgust, happiness, anger, and surprise. Persuaded by Darwin's research on emotions, these basic emotions have distinctive patterns of expression, antecedent & behaviors. Plutchik [9] on the other hand postulated a psycho-evolutionary theory of emotions with eight basic emotions that could blend to form new emotions. He organized these emotions in concentric circles with the intensity of emotions defining the position of these emotions, i.e. stronger emotions in the inner circle and weaker emotions in the outer circle. Also, the color of these discs varied with intensity. The darker the shade, the higher will be the intensity. Parrott[10] classified the emotions in a hierarchical system, putting over 100 emotions into basic, secondary, and tertiary emotions. The significance of such a deeper classification can be seen in applications like optimism detection in financial data where a basic set of emotions might be insufficient. As none of the three just-described emotion classifications included significant social emotions i.e., shame and guilt. So this study further includes one more noted emotion classification given by Izard [53]. Charles Darwin's evolutionary theory gave direction to Izard's study emphasizing basic emotions to be a part of one's biological inheritance. Popularly known as Differential Emotion Theory (DET), it lists ten basic categories of

emotions- fear, anger, shame, contempt, disgust, guilt, distress, interest, surprise, and joy. These fundamental categories of emotions can't be further broken down into simpler emotions, however, can be combined to form more emotions. He further suggested that each emotion is uniquely experienced with its unique neural basis. Table 1 presents the emotions present in the above-mentioned emotion classification models.

	Ekman	**Plutchik**	**Parrott**	**Izard**
	(M_i)	(M_j)	(M_k)	(M_l)
1	Anger	Anger	Anger	Anger
2	Fear	Fear	Fear	Fear
3	Joy	Joy	Joy	Joy
4	Surprise	Surprise	Surprise	Surprise
5	Sadness	Sadness	Sadness	Distress
6	Disgust	Disgust	Love	Disgust
7		Trust		Shame
8		Anticipation		Guilt
9				Contempt
10				Interest

Table 1: Emotion Classifications Models.

To take into account all of these emotion classifications, we take a union of primary emotion labels postulated by them as formulated below:

$M= M_i \cup M_j \cup M_k \cup M_l$

$1 \leq i \leq 6, 1 \leq j \leq 8, 1 \leq k \leq 6, 1 \leq l \leq 10$

$M=$ {anger, fear, joy, surprise, sadness, disgust, trust, anticipation, distress, love, shame, guilt, contempt, interest}

$M = \bigcup_{i=1}^{14} a_i$

Emo-Set $= \bigcup_{i=1}^{14} a_i$

Such that $a_i \in M$

From now on, we will refer to the obtained union set of emotion labels as "Emo-Set". Emo-Set contained a total of fourteen emotion labels. After defining Emo-Set, we present the methodology for the proposed work in Figure 1. The first section of methodology explains data collection. To collect Twitter data, we used the words present in Emo-Set as hashtags for the crawling procedure. From the crawled dataset, we extract original tweets that are not retweets of a tweet. Several data pre-processing steps were then carried out on these original tweets. The pre-processed tweets went through a data annotation pipeline as depicted in Figure 1. Data collection, pre-processing and annotation is explained in Section 3.2. Next, we compute the values for the different measurement constructs for each tweet, followed by the statistical analysis as described in Section 3.3 and 3.4 respectively.

3.2   Data collection and annotation

To investigate and evaluate the impact of emotions embedded in the content generated on social media

platforms, Twitter, a microblogging platform is considered as the source of data for our research. The current study used the distant supervision approach for data collection and annotation with an assumption that hashtags are a true representative of the author's emotions. We, therefore, retrieved the tweets and their metadata for exact matches of hashtags containing emotion words specified by Emo-Set to assemble the pool of data for our computational method. This resulted in a data trove containing 4, 99,185 tweets crawled between 29 June 2020 00:00 GMT and 12 Feb 2021 23:59 GMT. The data is occupying approximately 2.3 GB of uncompressed space stored in a MongoDB database system. For each tweet, the collected dataset included the following meta-data: publishing time, number of retweets, and number of favorites, and the account name of the sender. The sender's profile information was also recorded, including the number of followers, followees, background posts published on Twitter, and whether the account is verified. We then cleaned up our data by removing duplicate tweets (i.e., tweets with identical Twitter IDs). A few more steps were carried out as part of preprocessing pipeline like converting the tweet text to lowercase, replacing urls with keyword "URL", replacing media links with keyword "MEDIA" and removal of special as well as redundant characters. After these preprocessing steps, the dataset contained 3, 49,481 tweets. All messages in this dataset were written in English. Emphasis has been made to maintain user confidentiality in this research work. To minimize the potential harm, the usernames were replaced with pseudonyms and the messages published in this manuscript were paraphrased to prevent user recognition. Table 2 presents the statistics of the crawled dataset

Number of tweets	3,49, 481
Number of retweets	197, 862
Number of original tweets	1,51, 619
Number of users of original tweets	83,806

Table 2: Dataset Statistics.

In the real world, an individual may experience and thus express multiple emotions in their messages. In this case, the "message" would belong to the multiple emotions category. In our data set, the multi-emotion tweets, identified by multiple emotion hashtags constitute about 20% of the data. Thus, the emphasis has been put on multi-class as well as multi-label tweets while conducting the experimental investigation. To this end, the current work employed a similar approach as used by Colnericz and Demsar[54] to conduct experiments in two settings: Single-label Multi-class (SLMC) and Multilabel Multi-class (MLMC). In the SLMC setting, the first emotional hashtag is assigned as the target label, ignoring any additional emotional hashtags that appear later in the tweet. In MLMC, for each group of emotions, a vector is represented consisting of 0s and 1s.

3.3   Proposed measures of information diffusion

In line with previous studies [55]–[58], the current research work uses the number of likes and the number of
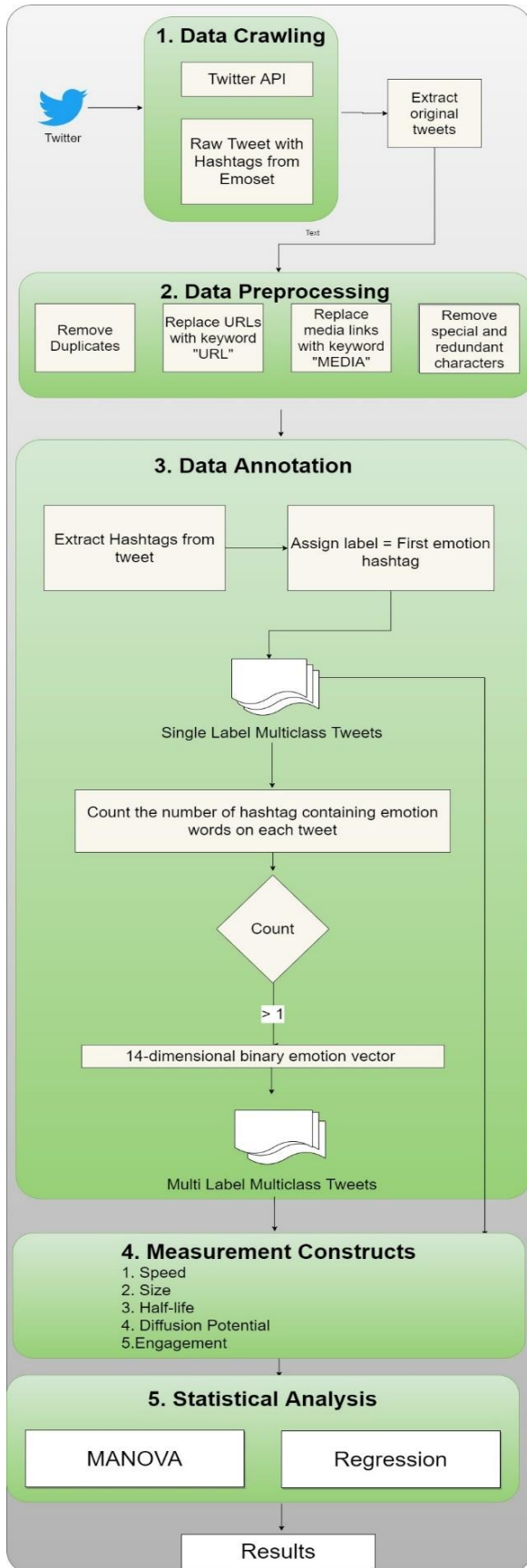
Figure 1: Methodology.

retweets obtained by a tweet as metrics to quantify the information diffusion process in terms of constructs defined in Figure 2.

Speed (First Diffusion): This continuous variable quantifies the time interval between tweet publication and its first retweet (as suggested in [5]). The unit used for the recording time interval in seconds. Let t_p be the tweet publication time and t_{r_i} be the time at which tweet received its ith retweet. So, the speed of the first diffusion will be calculated as:

First Diffusion (FD) $= t_{r_1} - t_p$, where t_{r_1} denotes the time at which the tweet received its first retweet.
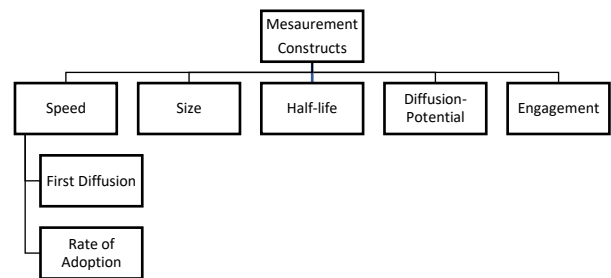

Figure 2: Measurement Constructs.

Speed (Rate of Adoption): Rate of adoption as speed measures the count of new retweets recorded by a given tweet per unit of time. A useful unit of time would be an interval that would readily analyze the fine-grained nature of the variable being measured while allowing the ease of mathematical calculation and interpretation. Some previous studies have advocated that a 12-hour period is appropriate to explain the dynamics of retweeting since it provides fair space for iterations of retweets and their progression [59]. The present study also used 12 hours as a unit of time since it recorded the overall trend of information propagation over time smoothing out minor jumps that can be confusing in longitudinal studies[60]. The Figure 3 presents the distribution of aggregated retweet count per 12 hours for original tweets.

The rate of diffusion is calculated using the first 48 hours after the tweet was published, with every 12 hours as a unit of time. The reason why the 48-hour interval was selected is that it denotes a statistically significant cut-off point (>=95% in the current case). This cut-off point (marked as dotted line in Figure 3) denotes the interval in the current data where more than 95 percent of the total retweets are achieved by the end of the 48th hour, minimizing the risk of speed inferences being skewed.

We calculate the Rate of Adoption (ROA) as follows:

$$\text{ROA} = \frac{\sum_{i=0}^{48} R_{c_t}}{4}, \text{ where } R_{c_t} \text{ refers to the total retweet count}$$

at time t.

Diffusion Size: Diffusion size measures the total count of retweets received by a tweet till the first 48 hours of its publication. It is a continuous variable whose values were skewed (Min=0 Max=927) and hence, log transformation was done to minimize the influence on significance testing
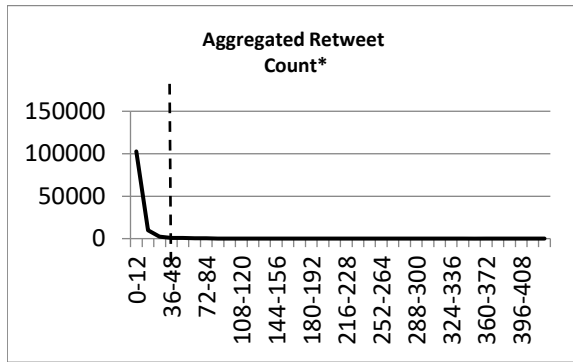
*The data for x-axis is shown for first few hours to solve the representation purpose.

Figure 3: Aggregated retweet count per 12-hour interval.

so statistical assumptions are not compromised [61], [62]. The Diffusion Size (SZ) is calculated as $\sum_{t=0}^{48} R_{c_t}$.

Half-life: A digital post whether it's on Facebook, Twitter, Reddit, LinkedIn, Instagram, or Pinterest, stays in that ecosystem for a very long time unless deleted or acted upon by a stakeholder. However, the relevance of that digital transaction is bound by the propagation speed by which it reaches a significant part of its total diffusion. To quantify this time-bound, half-life[2], analogous to radioactive decay is used in this research. The half-life of a tweet denotes the time in seconds at which the tweet has received 50 percent of its retweet count.

Half-life (HL) $= t_{r_{0.50 * R_c}}$, where R_c is the total number of retweets received by a tweet.

Diffusion potential: The half-life of a tweet gives the reflection of how effectively a tweet interacts with the user within a defined time threshold proportional to their life activity. However, the complete diffusion potential of a tweet could be translated as the amount of time required to achieve the statistically significant (95 percent in the current case), count of its retweets, before the rate of diffusion drops significantly.

Diffusion Potential (DP) is measured as:
$$DP = t_{r_{0.95 * R_c}}$$

Engagement: The number of likes obtained by a tweet also acts as an excellent proxy for measuring the diffusion process where users engage with the message by clicking the like button. This proxy variable should be handled differently than the retweet count. In the current study, we measure engagement as the count of favorites (likes) received by a tweet. It is also a continuous variable.
Table 3 describes the concepts and the measurements of all constructs. These constructs were used as dependent variables. The values for these constructs were log-transformed for further analysis to avoid long-tailed distributions. All the variables defined in Table 4 were used as independent variables in statistical analyses.

Construct	Var.	Measurement	Mean (SD)
First Diffusion	FD	Time interval (in seconds) between tweet posting time and its first retweet.	7570.06 (193866.1)
Rate of adoption	ROA	The number of new retweets per unit time recorded till 48 hours.	0.18 (1.89)
Size	SZ	The total count of retweets received a tweet till the 48th hour of its publication.	0.74 (7.54)
Half-Life	HL	Time (in seconds) in which a tweet has received 50 percent of its retweet count.	11109.53 (234524.3)
Diffusion potential	DP	Time (in seconds) taken to achieve 95% of its retweet count.	14713.61 (268439.9)
Engagement	EG	The total count of favorites (likes) received by a tweet.	4.09 (60.32)

* Var. = variable representation of a construct

Table 3: List of measurement constructs.

Construct	Var.	Measurement
Emotion	E	First emotion hashtag present in the tweet
URL	URL	Categorical variable for whether the tweet contains a URL
Media	M	Categorical variable for whether the tweet includes a media (image, audio or, video)
Follower	F	Number of followers
Total Emotions	TES	The total number of emotion hashtags present in the tweet (represented as 1s in vector)
Emotional Count	NPES	Number of negative and positive emotions as per NRC Lexicon

* Var. = variable representation of a construct

Table 4: List of independent variables.

3.4 Methods for statistical analysis

This section describes the statistical approach used for single-label multi-class and multi-label multi-class experiments.

Single-label Multi-class (SLMC) Analysis: The diffusion constructs, shown in Table 3 are used as dependent variables for our analysis. These variables are continuous and the independent variable, emotion (in Table 4) is categorical. So, a Multivariate Analysis of Variance (MANOVA) analysis is performed to investigate whether emotions were significantly associated with information diffusion or not. This explained the role of emotions on proposed information diffusion constructs, including speed (first-diffusion), speed (rate-of-adoption), size, half-life, diffusion potential, and engagement. Since we have multiple continuous dependent variables and one categorical independent variable, the choice for MANOVA analysis was justified. To carry out MANOVA analysis, the authors tested the bivariate correlation

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[2]   https://www.socialtalent.com/blog/recruitment/the-short-half-life-of-your-social-media-posts

between each of the diffusion constructs. The results of correlation analysis are reported in Table 5. Further, Tukey post hoc tests were performed to investigate the impact of emotions on each diffusion construct separately.

Multi-label Multi-class: A tweet may express a single dominant emotion or a range of emotions. In the MLMC experimental setting, we agreed to work with all of the emotions expressed in the tweet as hashtags. Here, a 14-dimensional binary vector is used to describe the emotional state of a tweet i.e. the presence or absence of the corresponding emotion {anger, fear, joy, surprise, sadness, disgust, trust, anticipation, distress, love, shame, guilt, contempt, interest} based on the hashtags present in a tweet.

Suppose, $ES_i = \{es_{i1}, es_{i2}, es_{i3}, es_{i4, \dots}, es_{i14}\}$ is the 14-dimensional emotional state vector for tweet t_i. The value for es_{ik} would be 1 if the tweet t_i represents the emotion k; else, 0. The existence of the appropriate emotion hashtag in a tweet is used to make this conclusion. For example, consider a tweet t_1 :

"*If People like You They Will Listen to You but If They #Trust You They will Do #Business With You!!! Looking for the best #exhibitionstand #design company visit: https://t.co/lYSEuQYvks #tradeshows #Scienceglobal #marketing #exhibition #love #trust #interest #quotes #fridaythoughts #thoughtsoftheday*"

The emotional state vector ES_1 for t_1 will be {0,0,0,0,0,0,1,0,0,1,0,0,01}. Further, to investigate whether multiple emotions present in a tweet jointly influence the information diffusion process, we performed regression analysis. For count-based diffusion constructs i.e. SZ and EG, negative binomial regression was performed because the variance of these variables is large. The remaining constructs were investigated using linear regression analysis. Following the work in Ref. [5], we used the presence of URLs and the number of followers as control variables since these influences have been shown to affect message diffusion. A categorical variable was

	RC	FC	HL	DP	ROA	TI
RC	1	.674**	.759**	.815**	.865**	.658**
FC	.674**	1	.520**	.560**	.660**	.445**
HL	.759**	.520**	1	.875**	.627**	.875**
DP	.815**	.560**	.875**	1	.686**	.848**
ROA	.865**	.660**	.627**	.686**	1	.506**
TI	.658**	.445**	.875**	.848**	.506**	1

Table 5: Bivariate correlation results among measurement constructs.

also added for the presence of media (image, audio or, video) as part of tweet content. We excluded a variable to represent the activity of Twitter users since it does not affect tweet diffusion. We used the variables defined in Table 3 as dependent variables and those defined in Table 4 were taken as independent variables. These statistical analyses were performed using SPSS version 26.

4 Results

This section reports descriptive results, outcomes obtained in SLMC as well as MLMC analysis.

4.1 Descriptive results

After contrived compilation and cleaning, our data pool consisted of 3, 49, 481 tweets posted by 2, 03, 803 users. Of the total 1, 51, 619 original tweets, only 28,495 (18.8%) received retweets. Among those who received retweets, the messages were retweeted as many as 927 times, and as few as 1 time (M=4.08, SD=17.353), suggesting a significant variation in the diffusion size.

The tweet messages received an average of 454 retweets per 12 hours in terms of speed (ROA), with more than half of them obtaining 7 or less retweets each 12 hours. Our findings were similar for the count of favorites (EG). More than half of the messages (55%) received no likes, while others drew a lot of attention from the public (number of likes=12,750). The distribution of diffusion results revealed a long-tail distribution, consistent with findings from prior research employing social media data (e.g. [65]), with fewer messages acquiring gradually higher popularity on Twitter. When it comes to emotions, we discovered that love was the most expressed emotion, whereas sadness was the least expressed.

4.2 SLMC outcomes

In this section, the authors perform MANOVA analysis to investigate the relationship between a tweet's primary emotion and its diffusion in the Twitter-sphere, eliminating the effects of any other factors affecting information diffusion. The relation between emotions and the diffusion process is measured through six constructs as defined in Table 3. The dependent variables were FD, ROA, SZ, HL, DP, and EG. We take Emotion (E) as defined in Table 4 as the independent variable.

After performing MANOVA, emotions were found to be a significant predictor of information diffusion. The Wilks Lambda row of results depicts F (78, 835870.8) = 73.17, p<0.0005, Wilks Lambda =0.963. Univariate testing indicated the significant effect of emotion on each of the six constructs, as reported in Table 6.

Next, Tukey HSD post hoc tests were used to examine the impact of emotions on each measurement constructs separately. Figure 4 depicts the effect of different emotion labels on the mean scores of each of the measurement constructs, separately.

As visualized from Figure 4, emotions such as joy, contempt, or guilt were found to be positively correlated with the diffusion process. Their presence led to higher diffusion size, faster first diffusion, and rate of adoption. Similarly, a higher half-life was observed in the presence of distress, joy, or contempt as a primary emotion. Distress also attained faster first diffusion and possessed stronger diffusion potential. On the other hand, anger, fear or, love led to weaker diffusion. Tweets containing anger, fear, or love as underlying emotion were found to have a lesser size of diffusion and a weaker rate of adoption. Also,

	Source	Type III Sum of Squares	df	Mean Square	F	Sig.
E	log_SZ	91.400	3	7.031	140.378	0.000
	log_FC	374.769	3	28.828	194.696	0.000
	log_HL	2672.920	3	205.609	120.439	0.000
	log_DP	3435.414	3	264.263	130.772	0.000
	log_ROA	24.034	3	1.849	138.185	0.000
	log_FD	1845.496	3	141.961	97.206	0.000

Table 6: The effect of emotionn on each construct separateely.

tweets infused with these emotions were reported to have a lower half-life and attained its first diffusion comparatively slower than other emotions.

Another observation was that tweets that captured the highest engagement contained joy as the primary emotion whereas those containing shame could capture lower engagement. Similar findings were reported in the related literature. Distress can induce different cognitive appraisals of online content, which is associated with readers' tendency to share. Online content with distress is often perceived as more helpful and valuable because distress indicates a higher level of the writer's cognitive efforts [63]. In contrast, anger leads to a lower level of perceived rationality of writers [64], and hence has a significant effect on diffusion outcomes.

Following the analysis of the data, it was discovered that tweets expressing joy consistently achieved greater and stronger diffusion in practically all diffusion dimensions. This might indicate that tweets with joy emotion spread a feeling of positivity and hence create a significant positive impact on the diffusion process. Even though positive emotions have a stronger impact on diffusion than negative ones, negative emotions are not free from leaving an imprint. The emotions of contempt and guilt are negative as per the NRC lexicon [65]. These emotions compel readers to share tweets more often as compared to other emotions. Tweets with a higher degree of distress are also associated with content spread by achieving faster first diffusion and stronger diffusion potential. Not only this, we can observe that anger and fear although attained lower impact on diffusion yet the impact was significant.

However, to further understand how different emotion categories influence the diffusion process, we report the multiple comparisons table for every dependent variable. Table 7 to 12 report multiple comparison results obtained in Tukey post hoc test for FD, ROA, SZ, HL, DP, and EG respectively. For example, Table 7 shows that for mean scores for SZ were statistically different between emotion pairs such as anger and disgust, anger and joy, fear and disgust, love and sadness, etc. These significant differences in mean scores between emotion pairs is depicted with asterisk (*) sign, indicating a p-value<0.0005. Other values without asterisk (*) sign are considered non-significant. These differences of impact created between non-significant emotion pairs are generally not much noticeable. For instance, as depicted

in Table 7, the impact of fear and anger as primary emotion on diffusion construct FD is similar(non-significant). This observation is also evident from our previous results i.e., anger and fear both as primary emotions had a low impact on diffusion construct FD. Content creators may take advantage by reading similar observations from Table 7-12.

4.3   MLMC outcomes

The SLMC analysis uncovered the role of primary emotion on information diffusion. However, it's a rarity that a person feels a single dominating emotion while writing a piece of text. When emotions co-exist, the dynamics of information diffusion become complex. Previous research work in this domain has not yet touched the impact of multiple emotions in depth, leaving a wide scope to uncover the truly complex nature of information diffusion. Hence, this study also looked at whether multiple emotions present in a tweet jointly influence the information diffusion process. More than often, multiple emotions find their way in expression, and thus they jointly influence the diffusion process. It becomes particularly difficult when a message elicits a range of emotions in its recipients, prompting them to share. We used regression analysis to figure out how multiple emotions affect the spread of social media posts.

First, we calculated a total emotion score (TES) for every tweet t_i in the following way:

$$TES_i = \sum_{m=1}^{14} es_{im}$$

For MLMC analysis, we considered only multi-label tweets i.e. 14>= TES>1. As a second step, we take the help of the NRC lexicon [65] to categorize the emotions in Emo-Set into positive, negative, and neutral. Negative emotions in Emo-Set = {anger, disgust, contempt, sadness, fear, guilt, shame, distress}. We refer to this set as NE. Positive emotions in Emo-Set = PE = {joy, love, interest}. Neutral emotions in Emo-Set= {surprise, trust, anticipation}.

We calculate a set of positive or negative emotions from Emo-Set as per the NRC lexicon [65].

$$NPE= NE \cup PE$$
$$TE= NE \cup PE \cup AE$$

Now, for each tweet t_i , we calculated a sum of all 1s for emotions present in NPE using the emotional state vector ES_i. We represented this score as $NPES_i$. Similarly, if we calculate a sum of 1s for emotions in TE for a tweet t_i , it will be same as TES_i.

We use NPES and TES as independent variables along with URL, M, and F in the regression model. The constructs defined in Table 3 are taken as dependent variables one by one. For SZ and EG, we use negative binomial regression.
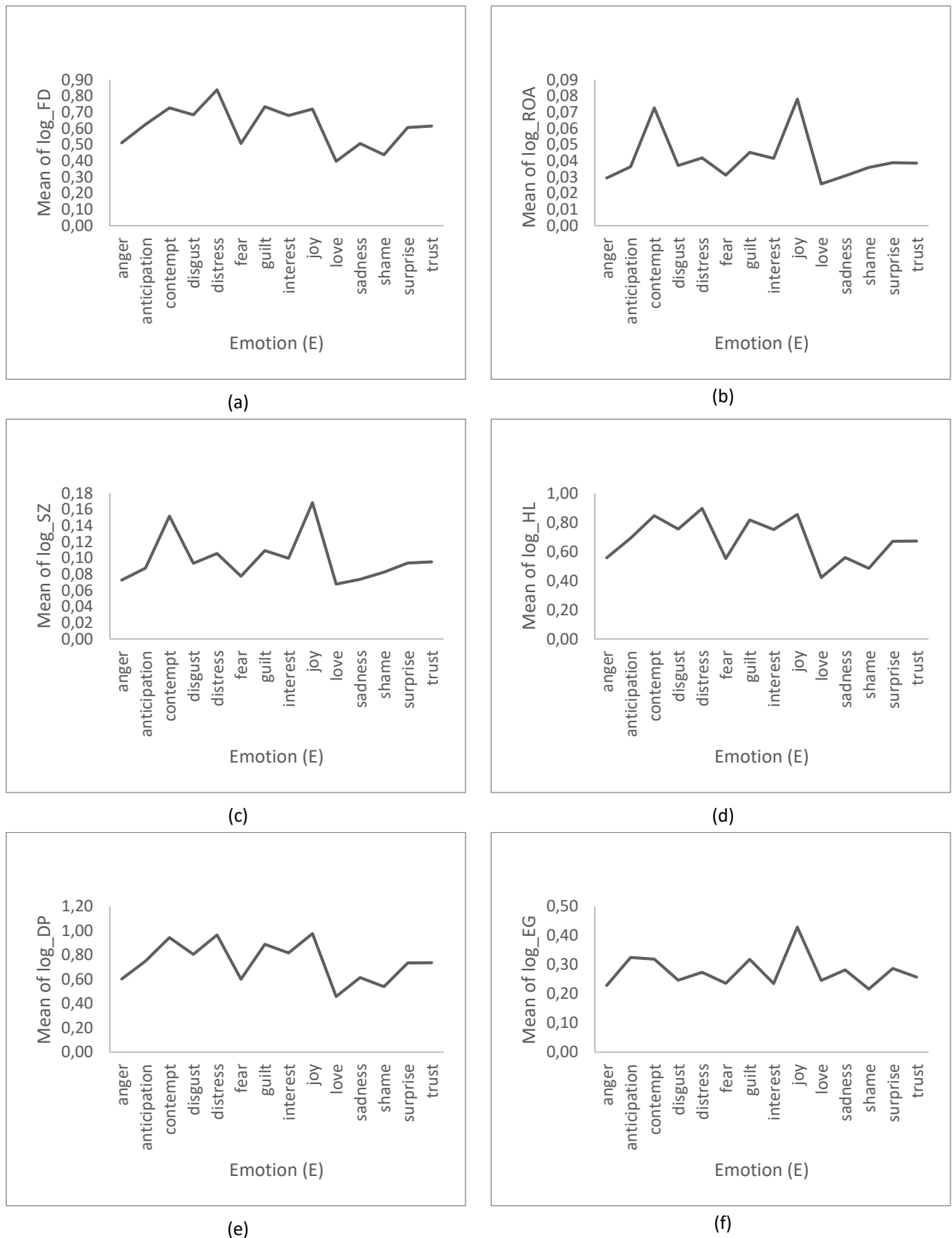
Figure 4: Effect of different emotion labels on the mean scores of each of the measurement constructs FD, ROA, SZ, HL, DP and EG respectively.

	anger	disgust	fear	joy	sadness	surprise	trust	antici-pation	love	distress	interest	shame	contempt	guilt
anger		-0.173*	0.004	-0.209*	0.004	-0.095*	-0.103*	-0.113*	0.115*	-0.327*	-0.169*	0.074*	-0.215*	-0.222*
disgust	0.173*		0.177*	-0.036	0.177*	0.078	0.07	0.059	0.287*	-0.154	0.004	0.247*	-0.042	-0.049
fear	-0.004	-0.177*		-0.213*	0	-0.099*	-0.107*	-0.118*	0.11*	-0.331*	-0.173*	0.07*	-0.219*	-0.226*
joy	0.209*	0.036	0.213*		0.213*	0.114*	0.106*	0.095	0.323*	-0.118*	0.04	0.283*	-0.006	-0.014
sadness	-0.004	-0.177*	0	-0.213*		-0.099*	-0.107*	-0.118*	0.11*	-0.331*	-0.173*	0.07*	-0.219*	-0.226*
surprise	0.095*	-0.078	0.099*	-0.114*	0.099*		-0.008	-0.019	0.209*	-0.232*	-0.074*	0.169*	-0.12*	-0.128*
trust	0.103*	-0.07	0.107*	-0.106*	0.107*	0.008		-0.011	0.217*	-0.224*	-0.066*	0.177*	-0.112*	-0.119*
anticipation	0.113*	-0.059	0.118*	-0.095	0.118*	0.019	0.011		0.228*	-0.213*	-0.055	0.188*	-0.101	-0.109
love	-0.114*	-0.287*	-0.11*	-0.323*	-0.11*	-0.209*	-0.217*	-0.228*		-0.441*	-0.283*	-0.04	-0.329*	-0.337*
distress	0.327*	0.154	0.331*	0.118*	0.331*	0.232*	0.224*	0.213*	0.441*		0.158*	0.401*	0.112	0.105
interest	0.169*	-0.004	0.173*	-0.04	0.173*	0.074*	0.066*	0.055	0.283*	-0.158*		0.243*	-0.046	-0.054
shame	-0.074*	-0.247*	-0.07*	-0.283*	-0.07*	-0.169*	-0.177*	-0.188*	0.04	-0.401*	-0.243*		-0.289*	-0.297*
contempt	0.215*	0.042	0.219*	0.006	0.219*	0.12*	0.112*	0.101	0.329*	-0.112	0.046	0.289*		-0.007
guilt	0.222*	0.049	0.226*	0.014	0.226*	0.128*	0.119*	0.109	0.337*	-0.105	0.054	0.297*	0.007	

Note: Asterisk(*) sign shows that the values are significant at $p<0.05$.

Table 7: Tukey's HSD Multiple Comparisons table for FD.

	anger	disgust	fear	joy	sadness	surprise	trust	antici-pation	love	distress	interest	shame	contempt	guilt
anger		-0.008	-0.002	-0.049*	-0.001	-0.009*	-0.009*	-0.007	0.004	-0.012*	-0.012*	-0.006*	-0.043*	-0.016*
disgust	0.008		0.006	-0.041*	0.006	-0.002	-0.001	0.001	0.011	-0.005	-0.004	0.001	-0.036*	-0.008
fear	0.002	-0.006		-0.047*	0	-0.008*	-0.007*	-0.005	0.005*	-0.011*	-0.01*	-0.005*	-0.042*	-0.014*
joy	0.049*	0.041*	0.047*		0.047*	0.039*	0.04*	0.042*	0.052*	0.036*	0.037*	0.042*	0.005	0.033*
sadness	0.001	-0.006	0	-0.047*		-0.008*	-0.008*	-0.006	0.005*	-0.011*	-0.011*	-0.005*	-0.042*	-0.014*
surprise	0.009*	0.002	0.008*	-0.039*	0.008*		0	0.003	0.013*	-0.003	-0.003	0.003	-0.034*	-0.006
trust	0.009*	0.001	0.007*	-0.04*	0.008*	0		0.002	0.013*	-0.003	-0.003	0.003	-0.034*	-0.007
anticipation	0.007	-0.001	0.005	-0.042*	0.006	-0.003	-0.002		0.011*	-0.006	-0.005	0	-0.036*	-0.009
love	-0.004	-0.011	-0.005*	-0.052*	-0.005*	-0.013*	-0.013*	-0.011*		-0.016*	-0.016*	-0.01*	-0.047*	-0.019*
distress	0.012*	0.005	0.011*	-0.036*	0.011*	0.003	0.003	0.006	0.016*		0	0.006	-0.031*	-0.003
interest	0.012*	0.004	0.01*	-0.037*	0.011*	0.003	0.003	0.005	0.016*	0		0.006*	-0.031*	-0.004
shame	0.006*	-0.001	0.005*	-0.042*	0.005*	-0.003	-0.003	0	0.01*	-0.006	-0.005*		-0.037*	-0.009*
contempt	0.043*	0.036*	0.042*	-0.005	0.042*	0.034*	0.034*	0.036*	0.047*	0.031*	0.031*	0.037*		0.028*
guilt	0.016*	0.008	0.014*	-0.033*	0.014*	0.006	0.007	0.009	0.019*	0.003	0.004	0.009*	-0.028*	

Note: Asterisk(*) sign shows that the values are significant at $p<0.05$.

Table 8: Tukey's HSD Multiple Comparisons table for ROA.

The relationship between the dependent and independent variables is described as follows in the negative binomial regression model:

$$log(SZ) = \beta_0 + \beta_1(URL) + \beta_2(M) + \beta_3(NPES) + \beta_4(log(F)) + \beta_5(TES)$$

$$SZ = e^{\beta_0} \times e^{\beta_1 URL} \times e^{\beta_2 M} \times e^{\beta_3 NPES} \times e^{\beta_4 F} \times e^{\beta_5 TES}$$

Here, β_n is the regression coefficient. It may be noted that since the distribution of the number of followers is heavy-tailed, variable F is log-transformed. Table 13 reports the results obtained after the application of the above model. It depicts the regression coefficient, β, and

the values for e^{β} for each independent variable. These values demonstrate the effect of each independent variable on SZ and EG respectively.

For the regression of the remaining constructs, we used a linear regression model. The dependent variables were FD, ROA, HL, and DP and the independent variables were TES, NPES, URL, M and F. Table 14 shows the results for linear regression. The results of the regression analysis showed that an increase in the number of positive or negative emotions increased the diffusion outcome. However, the addition of neutral emotions to the range of multiple emotions present in a tweet had a negative effect on diffusion outcome. Table 13 and 14 suggested that TE

	anger	disgust	fear	joy	sadness	surprise	trust	anticipation	love	distress	interest	shame	contempt	guilt
anger		-0.021	-0.005	-0.096*	-0.001	-0.021*	-0.023*	-0.015	0.005	-0.033*	-0.027*	-0.01*	-0.079*	-0.036*
disgust	0.021		0.016	-0.075*	0.02	0	-0.002	0.006	0.026	-0.012	-0.006	0.011	-0.058*	-0.016
fear	0.005	-0.016		-0.091*	0.004	-0.016*	-0.018*	-0.01	0.01*	-0.028*	-0.022*	-0.005	-0.074*	-0.032*
joy	0.096*	0.075*	0.091*		0.095*	0.075*	0.073*	0.081*	0.101*	0.063*	0.069*	0.086*	0.017	0.059*
sadness	0.001	-0.02	-0.004	-0.095*		-0.02*	-0.022*	-0.014	0.006	-0.032*	-0.026*	-0.009	-0.078*	-0.036*
surprise	0.021*	0	0.016*	-0.075*	0.02*		-0.002	0.006	0.026*	-0.012	-0.006	0.011*	-0.058*	-0.015*
trust	0.023*	0.002	0.018*	-0.073*	0.022*	0.002		0.008	0.028*	-0.01	-0.004	0.013*	-0.056*	-0.014
anticipation	0.015	-0.006	0.01	-0.081*	0.014	-0.006	-0.008		0.02*	-0.018	-0.012	0.005	-0.064*	-0.022
love	-0.005	-0.026	-0.01	-0.101*	-0.006	-0.026*	-0.028*	-0.02*		-0.038*	-0.032*	-0.015*	-0.084*	-0.041*
distress	0.033*	0.012	0.028*	-0.063*	0.032*	0.012	0.01	0.018	0.038*		0.006	0.023*	-0.046*	-0.004
interest	0.027*	0.006	0.022*	-0.069*	0.026*	0.006	0.004	0.012	0.032*	-0.006		0.017*	-0.052*	-0.01
shame	0.01*	-0.011	0.005	-0.086*	0.009	-0.011*	-0.013*	-0.005	0.015*	-0.023*	-0.017*		-0.069*	-0.027*
contempt	0.079*	0.058*	0.074*	-0.017	0.078*	0.058*	0.056*	0.064*	0.084*	0.046*	0.052*	0.069*		0.043*
guilt	0.036*	0.016	0.032*	-0.059*	0.036*	0.015*	0.014	0.022	0.041*	0.004	0.01	0.027*	-0.043*	

Table 9: Tukey's HSD Multiple Comparisons table for SZ.

	anger	disgust	fear	joy	sadness	surprise	trust	anticipation	love	distress	interest	shame	contempt	guilt
anger		-0.197*	0.005	-0.297*	-0.002	-0.114*	-0.115*	-0.134*	0.135*	-0.339*	-0.194*	0.073*	-0.29*	-0.259*
disgust	0.197*		0.202*	-0.099	0.195*	0.084	0.083	0.063	0.333*	-0.141	0.004	0.27*	-0.092	-0.062
fear	-0.005	-0.202*		-0.301*	-0.007	-0.119*	-0.119*	-0.139*	0.13*	-0.343*	-0.198*	0.068*	-0.295*	-0.264*
joy	0.297*	0.099	0.301*		0.294*	0.183*	0.182*	0.162*	0.432*	-0.042	0.103*	0.369*	0.007	0.037
sadness	0.002	-0.195*	0.007	-0.294*		-0.112*	-0.112*	-0.132*	0.137*	-0.336*	-0.191*	0.075*	-0.288*	-0.257*
surprise	0.114*	-0.084	0.119*	-0.183*	0.112*		-0.001	-0.02	0.249*	-0.225*	-0.08*	0.187*	-0.176*	-0.145*
trust	0.115*	-0.083	0.119*	-0.182*	0.113*	0.001		-0.019	0.25*	-0.224*	-0.079*	0.188*	-0.175*	-0.144*
anticipation	0.134*	-0.063	0.139*	-0.162*	0.132*	0.02	0.019		0.269*	-0.205*	-0.059	0.207*	-0.156*	-0.125
love	-0.135*	-0.333*	-0.13*	-0.432*	-0.137*	-0.249*	-0.25*	-0.269*		-0.474*	-0.329*	-0.062*	-0.425*	-0.394*
distress	0.339*	0.141	0.343*	0.042	0.336*	0.225*	0.224*	0.205*	0.474*		0.145*	0.411*	0.049	0.08
interest	0.194*	-0.004	0.198*	-0.103*	0.191*	0.08	0.079	0.059	0.329*	-0.145*		0.266*	-0.096	-0.066
shame	-0.073*	-0.27*	-0.068*	-0.369*	-0.075*	-0.187*	-0.187*	-0.207*	0.062*	-0.411*	-0.266*		-0.363*	-0.332*
contempt	0.29*	0.092	0.295*	-0.007	0.288*	0.176*	0.175*	0.156*	0.425*	-0.049	0.096	0.363*		0.031
guilt	0.259*	0.062	0.264*	-0.037	0.257*	0.145*	0.144*	0.125	0.394*	-0.08	0.066	0.332*	-0.031	

Note: Asterisk(*) sign shows that the values are significant at $p < 0.05$.

Table 10: Tukey's HSD Multiple Comparisons table for HL.

i.e. the set of emotions containing one or more neutral emotions decreased the diffusion outcome (SZ, EG, HL, DP, FD and ROA respectively, $p < 0.01$)). Additionally, the presence of emotions from set NPE increased the diffusion results. Other independent variables, for example, follower, media and URL too had a significant impact on diffusion. Variable F and URL positively affected the dependent variables.

To demonstrate the effects of each independent variable on the dependent variable, the values for regression coefficient, β for each variable are provided in the Table 14.

	anger	disgust	fear	joy	sadness	surprise	trust	anticipation	love	distress	interest	shame	contempt	guilt
anger		-0.202*	0.003	-0.373*	-0.01	-0.131*	-0.134*	-0.148*	0.145*	-0.361*	-0.214*	0.063*	-0.34*	-0.286*
disgust	0.202*		0.205*	-0.171*	0.191*	0.07	0.067	0.054	0.347*	-0.16	-0.013	0.265*	-0.139	-0.084
fear	-0.003	-0.205*		-0.376*	-0.013	-0.134*	-0.137*	-0.151*	0.142*	-0.364*	-0.217*	0.06*	-0.343*	-0.289*
joy	0.373*	0.171*	0.376*		0.362*	0.241*	0.239*	0.225*	0.518*	0.011	0.158*	0.436*	0.032	0.087
sadness	0.01	-0.191*	0.013	-0.362*		-0.121*	-0.124*	-0.137*	0.155*	-0.351*	-0.204*	0.074*	-0.33*	-0.275*
surprise	0.131*	-0.07	0.134*	-0.241*	0.121*		-0.003	-0.016	0.276*	-0.23*	-0.083*	0.195*	-0.209*	-0.154*
trust	0.134*	-0.067	0.137*	-0.239*	0.124*	0.003		-0.013	0.279*	-0.227*	-0.08*	0.197*	-0.206*	-0.151*
anticipation	0.148*	-0.054	0.151*	-0.225*	0.137*	0.016	0.013		0.293*	-0.214*	-0.067	0.211*	-0.193*	-0.138
love	-0.145*	-0.347*	-0.142*	-0.518*	-0.155*	-0.276*	-0.279*	-0.293*		-0.506*	-0.359*	-0.082*	-0.485*	-0.431*
distress	0.361*	0.16	0.364*	-0.011	0.351*	0.23*	0.227*	0.214*	0.506*		0.147*	0.424*	0.021	0.076
interest	0.214*	0.013	0.217*	-0.158*	0.204*	0.083*	0.08*	0.067	0.359*	-0.147*		0.277*	-0.126	-0.071
shame	-0.063*	-0.265*	-0.06	-0.436*	-0.074*	-0.195*	-0.197*	-0.211*	0.082*	-0.424*	-0.277*		-0.404*	-0.349*
contempt	0.34*	0.139	0.343*	-0.032	0.33*	0.209*	0.206*	0.193*	0.485*	-0.021	0.126	0.404*		0.055
guilt	0.286*	0.084	0.289*	-0.087	0.275*	0.154*	0.151*	0.138	0.431*	-0.076	0.071	0.349*	-0.055	

Note: Asterisk(*) sign shows that the values are significant at p<0.05.

Table 11: Tukey's HSD Multiple Comparisons table for DP.

	anger	disgust	fear	joy	sadness	surprise	trust	anticipation	love	distress	interest	shame	contempt	guilt
anger		-0.018	-0.008	-0.2*	-0.053*	-0.058*	-0.029*	-0.096*	-0.017*	-0.045*	-0.007	0.012	-0.09*	-0.089*
disgust	0.018		0.011	-0.182*	-0.035	-0.04	-0.011	-0.078*	0.001	-0.026	0.012	0.031	-0.072*	-0.071*
fear	0.008	-0.011		-0.193*	-0.046*	-0.051*	-0.022*	-0.089*	-0.01	-0.037*	0.001	0.02*	-0.083*	-0.082*
joy	0.2*	0.182*	0.193*		0.147*	0.142*	0.171*	0.104*	0.183*	0.155*	0.194*	0.213*	0.11*	0.111*
sadness	0.053*	0.035	0.046*	-0.147*		-0.005	0.024*	-0.043*	0.036*	0.008	0.047*	0.066*	-0.037*	-0.036*
surprise	0.058*	0.04	0.051*	-0.142*	0.005		0.029*	-0.038*	0.041*	0.014	0.052*	0.071*	-0.032	-0.031*
trust	0.029*	0.011	0.022*	-0.171*	-0.024*	-0.029*		-0.067*	0.012*	-0.016	0.023*	0.042*	-0.061*	-0.06*
anticipation	0.096*	0.078*	0.089*	-0.104*	0.043*	0.038*	0.067*		0.079*	0.051*	0.09*	0.109*	0.006	0.007
love	0.017*	-0.001	0.01	-0.183*	-0.036*	-0.041*	-0.012*	-0.079*		-0.028	0.011	0.03*	-0.073*	-0.072*
distress	0.045*	0.026	0.037*	-0.155*	-0.008	-0.014	0.016	-0.051*	0.028		0.038*	0.057*	-0.045	-0.044*
interest	0.007	-0.012	-0.001	-0.194*	-0.047*	-0.052*	-0.023*	-0.09*	-0.011	-0.038*		0.019*	-0.084*	-0.083*
shame	-0.012	-0.031	-0.02*	-0.213*	-0.066*	-0.071*	-0.042*	-0.109*	-0.03*	-0.057*	-0.019*		-0.103*	-0.102*
contempt	0.09*	0.072*	0.083*	-0.11*	0.037*	0.032	0.061*	-0.006	0.073*	0.045	0.084*	0.103*		0.001
guilt	0.089*	0.071*	0.082*	-0.111*	0.036*	0.031*	0.06*	-0.007	0.072*	0.044*	0.083*	0.102*	-0.001	

Note: Asterisk(*) sign shows that the values are significant at p<0.05.

Table 12: Tukey's HSD Multiple Comparisons table for EG.

5 Discussion

5.1 Findings and limitations

Through different analyses, the current work showed that emotions are indeed an important factor in social media content diffusion. As discussed in Section 2, there is strong evidence of the existence of positivity as well as negativity bias on social media. Also, most of the related studies targeted domain-specific tweets, and as discussed in Ref [5], the tweet domain alters how a tweet's emotion affects its diffusion process. However, after excluding the influence of tweet domains, our research examined the

Independent variables	Dependent variable			
	SZ		EG	
	β	e^{β}	β	e^{β}
URL	0.539	1.714	0.828	2.289
M	-0.538	0.584	-0.412	0.662
NPES	0.389	1.476	0.113	1.120
log(F)	0.791	2.206	0.788	2.199
TES	-0.864	0.421	-0.445	0.634
Pseudo R^2	0.026		0.022	

Table 13: Negative Binomial Regression results for SZ and EG.

impact of emotions found in a tweet on its diffusion. After looking at the results obtained in SLMC analysis, it is clear that positive tweets especially those containing joy as primary emotion are generally more viral, which supports positivity bias on social media. Also, several negative emotions like contempt, guilt, or distress achieved stronger and faster diffusion indicating a negativity bias. Thus, instead of supporting the theories of positivity and negativity bias, we infer certain emotions (positive or negative) had a significant impact on social media information diffusion. For tweets containing more than one emotion, regression results indicated that the presence of multiple positive emotions, numerous negative emotions or a blend of two or more positive or negative emotions increased the diffusion outcomes. However, the addition of one or more neutral emotions such as surprise, trust, and anticipation led to lower diffusion results. Looking at the other independent factors, we can see that follower, URL, and media had significant impact on all of the diffusion constructs, as found in other studies[5][45][44].

The methodology of the current research differs from the previous studies in the following ways:

- **Set of Emotions**
  To form a uniform basis of analysis, we based the proposed work on an exhaustive set of 14 emotions, Emo-Set. This set of emotions represent the universe for this study. Emo-Set contains a good mix of positive, negative and neutral emotions. To create an unbiased research study, we used this Emo-Set for data crawling and further analysis. The dataset acquired using this set was independent of any domain, event or time. The SLMC analysis shed a light on the role of emotions in information diffusion on Twitter. The previous research work has a divide on polarity of emotions with either positivity bias or negativity bias being considered as the driver of diffusion. The effect of primary emotion was studied on diffusion process using MANOVA analysis. The results of the analysis showed that both positive and negative emotions led to positive influence on diffusion. In MLMC analysis, the 14-dimensional emotion vector was created for every tweet based on the presence/absence of emotions from Emo-Set. These vectors were then compared for the presence of positive, negative and ambiguous emotions.

Independent variables	Dependent Variable			
	HL	DP	FD	ROA
	β	β	β	β
constant	0.214	0.173	0.276	0.003
URL	-0.227	-0.291	-0.165	-0.03
M	0.301	0.361	0.242	0.033
NPES	0.135	0.167	0.112	0.114
log(F)	0.382	0.456	0.312	1.038
TES	-0.369	-0.436	-0.324	-0.238
R^2	0.134	0.162	0.104	0.205

Table 14: Linear Regression results for HL, DP, FD, and ROA.

- **Domain Independence**
  The methodology used for this analysis used multiple constructs that reflect the diffusion behavior of the tweet. Previously, a lot of studies has focused on domain (health, politics, etc) for the analysis. We modeled the data with independence to domain, time of a tweet and other factors, keeping the analysis focused on single or multiple emotions present in a tweet.

- **Impact of single and multiple emotions**
  This is the first study as per the author's knowledge which considers the impact of both single as well as multiple emotions present in a tweet text on its diffusion behavior. The results of MLMC analysis uncovered the multi-emotion nature of tweets and its impact on information diffusion. When a tweet has multiple emotions present in it, it becomes very difficult to analyze the effect since the number and nature of emotions vary. For this, we used the total number of positive and negative emotions and ambiguous emotions (TES) and the total number of positive and negative emotions (NPES) as parameters to analyze the diffusion dynamics of a tweet.

- **Constructs**
  The methodology of this paper presented six different constructs to uncover the dynamics of social media content diffusion. These include speed (first diffusion, rate of adoption), size, half-life, diffusion potential and engagement. All these constructs together highlighted very useful characteristics of social media content.

Table 15 presents a simple comparison based on the proposed methodology with previous studies.

5.2 Limitations

While we have tried to inculcate all the best practices to present unbiased research and outcomes of our study, yet, we are also not untouched by certain limitations. First, the study has focused upon only one social media platform-Twitter. Though the results from the study of one social media platform will be quite applicable over other social media channels as well, however, the platform's function and policies, such as keyword census and

Ref.	Platform	Emotions	Domain-independent	Single-label Or Multi-label	Speed	Size	Half-life	Diffusion-potential
[5]	Twitter	Positive, Negative	No, Politics	Single-label	Yes	Yes	No	No
[32]	Instagram	Hope, Fear, Joy, Sadness	No, Cancer	Single-label	No	No	No	No
[42]	Twitter	Hope, Fear, Sadness, Anger, Happiness	No, Cancer	Single-label	No	Yes	No	No
[43]	Twitter	Joy, Anger, Fear, Sadness, bittersweet, hope	No, Cancer	Single-label	No	Yes	No	No
[44]	Twitter	Fear, Sadness, Anger	No, Cancer	Single-label	No	Yes	No	No
[45]	Weibo	Fear, Hope	No, Cancer	Single-label	No	Yes	No	No
PS	Twitter	Emo-Set	Yes	Single-label + Multi-label	Yes	Yes	Yes	Yes

*PS= Proposed Study

Table 15: Comparison with related studies.

recommendation algorithms, may restrict the generalizability of the findings. The current study might be replicated in other social media platforms in the future. Second, parallel research in psychology hasn't yet reached an agreement on the basic discrete emotion categories for human beings. We have worked and focused on four different emotion classification models. These models are well defined and accepted across the scientific community as well as expressed commonly in online content. Future research may investigate the inclusiveness of different emotion classification models, their impact on the diffusion process, and how these interact with social and psychological processes. Also, upcoming research may investigate the link between psychological processes and the relationships we observed. For example- why certain individuals are more likely to spread a certain kind of content with predominantly similar emotional inclination and how social ties affect this link. Furthermore, it may also be important to explore the relation between context and emotions in social media messages and their diffusion. Understanding this will better inform content producers to write and promote their work on social media.

6 Conclusion

The current study investigated the relationship between the emotion(s) of a tweet and its diffusion. We utilized several measurement constructs to analyze the diffusion outcomes. As a message may have a single emotion or several different emotions, the experimentation of the proposed study was carried out in both single-label as well as multi-label settings. We found that certain emotions both positive (joy) as well as negative (contempt, guilt, or distress) attained faster and stronger diffusion as primary emotions. In contrast, tweets infused with primary emotions like anger or fear led to a lower yet significant impact on information diffusion. Additionally, information diffusion was positively correlated with multiple positive emotions, multiple negative emotions, or a mixture of two or more positive or negative emotions. Adding one or more neutral emotions to the collection of emotions stated in a tweet, on the other hand, had a

detrimental influence on information dissemination. The findings will be useful to practitioners such as social networking managers, content authors, and advertisers. To begin, users may employ emotions like joy and contempt, contained in social media content to stimulate the spreading of online information like news items, commercial promotions, and political campaigns.

References

[1] L. McShane, E. Pancer, M. Poole, and Q. Deng, "Emoji, Playfulness, and Brand Engagement on Twitter," *J. Interact. Mark.*, vol. 53, pp. 96–110, 2021.
https://doi.org/10.1016/j.intmar.2020.06.002

[2] S. P, S. Niduthavolu, and L. N. Vedanthachari, "Analysis of content strategies of selected brand tweets and its influence on information diffusion," *J. Adv. Manag. Res.*, 2020.
https://doi.org/10.1108/jamr-06-2020-0107

[3] J. P. Forgas, *Emotion and social judgments*, no. 23. Psychology Press, 1991.

[4] R. Briones, X. Nan, K. Madden, and L. Waks, "When vaccines go viral: an analysis of HPV vaccine coverage on YouTube," *Health Commun.*, vol. 27, no. 5, pp. 478–485, 2012.
https://doi.org/10.1080/10410236.2011.610258

[5] S. Stieglitz and L. Dang-Xuan, "Emotions and Information Diffusion in Social Media—Sentiment of Microblogs and Sharing Behavior," *J. Manag. Inf. Syst.*, vol. 29, no. 4, pp. 217–248, 2013.
https://doi.org/10.2753/mis0742-1222290408

[6] Berger, Jonah, and Katherine L. Milkman. "Emotion and virality: what makes online content go viral?." *NIM Marketing Intelligence Review* 5.1,2013.
https://doi.org/10.2478/gfkmir-2014-0022

[7] C. A. Smith and P. C. Ellsworth, "Patterns of cognitive appraisal in emotion.," *J. Pers. Soc. Psychol.*, vol. 48, no. 4, p. 813, 1985.

[8] P. Ekman, "An argument for basic emotions," *Cogn. Emot.*, vol. 6, no. 3–4, pp. 169–200, 1992.

[9] R. Plutchik, "A general psychoevolutionary theory of emotion," *Theor. Emot.*, vol. 1, no. 3–31, p. 4, 1980.

[10] W. G. Parrott, *Emotions in social psychology: Essential readings*. Psychology Press, 2001.

[11] C. E. Izard, D. Z. Libero, P. Putnam, and O. M. Haynes, "Stability of emotion experiences and their relations to traits of personality.," *J. Pers. Soc. Psychol.*, vol. 64, no. 5, pp. 847–860, 1993.

[12] L. Zhang, M. Luo, and R. J. Boncella, "Product information diffusion in a social network," *Electron. Commer. Res.*, vol. 20, no. 1, pp. 3–19, 2020.

[13] W. Wang and W. N. Street, "Modeling and maximizing influence diffusion in social networks for viral marketing," *Appl. Netw. Sci.*, vol. 3, no. 1, pp. 1–26, 2018.
https://doi.org/10.1007/s41109-018-0062-7

[14] S. G. Kulkarni, A. Bilgi, D. Miskin, R. Oursang, P. G. S. Hiremath, and N. T. Pendari, "Spheres of influence for effective viral marketing," in *2018 International Conference on Advances in Computing, Communication Control and Networking (ICACCCN)*, 2018, pp. 750–753.
https://doi.org/10.1109/icacccn.2018.8748456

[15] A. Banerjee, A. G. Chandrasekhar, E. Duflo, and M. O. Jackson, "The diffusion of microfinance," *Science (80-.).*, vol. 341, no. 6144, 2013.
https://doi.org/10.1126/science.1236498

[16] S. Mitra and S. Ransbotham, "Information disclosure and the diffusion of information security attacks," *Inf. Syst. Res.*, vol. 26, no. 3, pp. 565–584,2015.
https://doi.org/10.1287/isre.2015.0587

[17] S. Ransbotham and S. Mitra, "The impact of immediate disclosure on attack diffusion and volume," in *Economics of Information Security and Privacy III*, Springer, 2013, pp. 1–12.
https://doi.org/10.1007/978-1-4614-1981-5_1

[18] X. Shi, K. Fernandes, and P. Chumnumpan, "Diffusion of multi-generational high-technology products," *Technovation*, vol. 34, no. 3, pp. 162–176,2014.
https://doi.org/10.1016/j.technovation.2013.11.008

[19] Rehman, A. U., Jiang, A., Rehman, A., Paul, A., & Sadiq, M. T, " Identification and role of opinion leaders in information diffusion for online discussion network. Journal of Ambient Intelligence and HumanizedComputing",1-13,2020.
https://doi.org/10.1007/s12652-019-01623-5

[20] B. Rime, B. Mesquita, S. Boca, and P. Philippot, "Beyond the emotional event: Six studies on the social sharing of emotion," *Cogn. Emot.*, vol. 5, no.5–6,pp.435–465,1991.
https://doi.org/10.1080/02699939108411052

[21] J. Berger and K. L. Milkman, "What makes online content viral?," *J. Mark. Res.*, vol. 49, no. 2, pp. 192–205,2012.
https://doi.org/10.1509/jmr.10.0353

[22] C. Heath, C. Bell, and E. Sternberg, "Emotional selection in memes: the case of urban legends.," *J. Pers. Soc. Psychol.*, vol. 81, no. 6, p. 1028, 2001.
https://doi.org/10.1037/0022-3514.81.6.1028

[23] M. Sinaceur, C. Heath, and S. Cole, "Emotional and deliberative reactions to a public crisis: Mad cow disease in France," *Psychol. Sci.*, vol. 16, no. 3,pp.247–254,2005.
https://doi.org/10.1111/j.09567976.2005.00811.x

[24] J. L. Robertson and J. Barling, "Greening organizations through leaders' influence on employees' pro-environmental behaviors," *J. Organ. Behav.*, vol. 34, no. 2, pp. 176–194, 2013.
https://doi.org/10.1002/job.1820

[25] L. Reinecke and S. Trepte, "Authenticity and well-being on social network sites: A two-wave longitudinal study on the effects of online authenticity and the positivity bias in SNS communication," *Comput. Human Behav.*, vol. 30, pp. 95–102, 2014.
https://doi.org/10.1016/j.chb.2013.07.030

[26] S. Trepte, T. Dienlin, and L. Reinecke, "Risky behaviors: How online experiences influence privacy behaviors," *Von Der Gutenberg-Galaxis Zur Google-Galaxis. From Gutenb. Galaxy to GoogleGalaxy*,2014.

[27] E. Ferrara and Z. Yang, "Measuring emotional contagion in social media," *PLoS One*, vol. 10, no. 11,p.e0142390,2015.
https://doi.org/10.1371/journal.pone.0142390

[28] E. Ferrara and Z. Yang, "Quantifying the effect of sentiment on information diffusion in social media," *PeerJ Comput. Sci.*, vol. 1, p. e26, 2015.
https://doi.org/10.7717/peerj-cs.26

[29] E. Joyce and R. E. Kraut, "Predicting continued participation in newsgroups," *J. Comput. Commun.*, vol. 11, no. 3, pp. 723–747, 2006.

[30] S.-M. Chen, J. Fang, L.-M. Wang, and C.-L. Liu, "Rest a while and run a mile: Relationship between distraction and negative emotions among college students in China," *PLoS One*, vol. 15, no. 9,p.e0236030,2020.
https://doi.org/10.1371/journal.pone.0236030

[31] P. Rozin and E. B. Royzman, "Negativity bias, negativity dominance, and contagion," *Personal. Soc. Psychol. Rev.*, vol. 5, no. 4, pp. 296–320, 2001.
https://doi.org/10.1207/s15327957pspr0504_2

[32] X. Zhu, Y. Kim, and H. Park, "Do messages spread widely also diffuse fast? Examining the effects of message characteristics on information diffusion," *Comput. Human Behav.*, vol. 103, pp. 37–47,2020.
https://doi.org/10.1016/j.chb.2019.09.006

[33] S. J. Park, Y. S. Lim, and H. W. Park, "Comparing Twitter and YouTube networks in information diffusion: The case of the 'Occupy Wall Street' movement," *Technol. Forecast. Soc. Change*, vol. 95,pp.208–217,2015.
https://doi.org/10.1016/j.techfore.2015.02.003

[34] R. Pfitzner, A. Garas, and F. Schweitzer, "Emotional divergence influences information spreading in Twitter," *ICWSM 2012 - Proc. 6th Int. AAAI Conf. Weblogs Soc. Media*, pp. 543–546, 2012
https://doi.org/10.1890/1000968123489077700

[35] R. Pfitzner, A. Garas, and F. Schweitzer, "Emotional divergence influences information spreading in

twitter," in *Proceedings of the International AAAI Conference on Web and Social Media*, 2012, vol. 6, no. 1.
https://doi.org/10.1890/1000968123489077700

[36] A. L. Hill, D. G. Rand, M. A. Nowak, and N. A. Christakis, "Infectious disease modeling of social contagion in networks," *PLoS Comput Biol*, vol. 6,no.11,p.e1000968,2010.
https://doi.org/10.1371/journal.pcbi.1000968

[37] S. Chen, J. Mao, G. Li, C. Ma, and Y. Cao, "Uncovering sentiment and retweet patterns of disaster-related tweets from a spatiotemporal perspective – A case study of Hurricane Harvey," *Telemat. Informatics*, vol. 47, no. June 2019, p. 101326,2020.
https://doi.org/10.1016/j.tele.2019.101326

[38] J. P. Dillard and K. Seo, "Affect and persuasion," *SAGE Handb. Persuas. Dev. theory Pract.*, pp. 150–166, 2013.

[39] E. Kim, J. Hou, J. Y. Han, and I. Himelboim, "Predicting retweeting behavior on breast cancer social networks: Network and content characteristics," *J. Health Commun.*, vol. 21, no. 4,pp.479–486,2016.
https://doi.org/10.1080/10810730.2015.1103326

[40] W. J. Brady, J. A. Wills, J. T. Jost, J. A. Tucker, and J. J. Van Bavel, "Emotion shapes the diffusion of moralized content in social networks," *Proc. Natl. Acad. Sci.*, vol. 114, no. 28, pp. 7313–7318, 2017.
https://doi.org/10.1073/pnas.1618923114

[41] H.-J. Paek, S.-H. Oh, and T. Hove, "How fear-arousing news messages affect risk perceptions and intention to talk about risk," *Health Commun.*, vol. 31, no. 9, pp. 1051–1062, 2016.
https://doi.org/10.1080/10410236.2015.1037419

[42] J. G. Myrick, A. E. Holton, I. Himelboim, and B. Love, "#Stupidcancer: Exploring a Typology of Social Support and the Role of Emotional Expression in a Social Media Community," *Health Commun.*, vol. 31, no. 5, pp. 596–605, 2016.
https://doi.org/10.1080/10410236.2014.981664

[43] Z. Wang, H. Liu, W. Liu, and S. Wang, "Understanding the power of opinion leaders' influence on the diffusion process of popular mobile games: Travel Frog on Sina Weibo," *Comput. Human Behav.*, vol. 109, p. 106354, 2020.
https://doi.org/10.1016/j.chb.2020.106354

[44] X. Wang and E. W. J. Lee, "Negative emotions shape the diffusion of cancer tweets: toward an integrated social network–text analytics approach," *Internet Res.*, vol. 2, 2020.
https://doi.org/10.1108/intr-04-2020-0181

[45] X. Wang, L. Chen, J. Shi, and T. Q. Peng, "What makes cancer information viral on social media?," *Comput. Human Behav.*, vol. 93, no. October 2018,pp.149–156,2019.
https://doi.org/10.1016/j.chb.2018.12.024

[46] X. Wang, L. Chen, J. Shi, and T.-Q. Peng, "What makes cancer information viral on social media?," *Comput. Human Behav.*, vol. 93, pp. 149–156, 2019.
https://doi.org/10.1016/j.chb.2018.12.024

[47] J. Shin, L. Jian, K. Driscoll, and F. Bar, "The diffusion of misinformation on social media: Temporal pattern, message, and source," *Comput. Human Behav.*, vol. 83, pp. 278–287, 2018.
https://doi.org/10.1016/j.chb.2018.02.008

[48] J. Yang and S. Counts, "Predicting the speed, scale, and range of information diffusion in twitter," in *Proceedings of the International AAAI Conference on Web and Social Media*, 2010, vol. 4,no.1.
https://ojs.aaai.org/index.php/ICWSM/article/view/14039

[49] L. Zhang and T.-Q. Peng, "Breadth, depth, and speed: diffusion of advertising messages on microblogging sites," *Internet Res.*, 2015.
https://doi.org/10.1108/intr-01-2014-0021

[50] E. M. Rogers, *Diffusion of innovations*. Simon and Schuster, 2010.

[51] K. F. Kee, L. Sparks, D. C. Struppa, M. A. Mannucci, and A. Damiano, "Information diffusion, Facebook clusters, and the simplicial model of social aggregation: a computational simulation of simplicial diffusers for community health interventions," *Health Commun.*, vol. 31, no.4,pp.385–399,2016.
https://doi.org/10.1080/10410236.2014.960061

[52] X. Zhu, Y. Kim, and H. Park, "Do messages spread widely also diffuse fast? Examining the effects of message characteristics on information diffusion," *Comput. Human Behav.*, vol. 103, no. September2019,pp.37–47,2020.
https://doi.org/10.1016/j.chb.2019.09.006

[53] C. E. Izard, "Basic emotions, relations among emotions, and emotion-cognition relations.," 1992.

[54] N. Colneric and J. Demsar, "Emotion Recognition on Twitter: Comparative Study and Training a Unison Model," *IEEE Trans. Affect. Comput.*, vol. 3045, no. c, pp. 1–1, 2018.
https://doi.org/10.1109/taffc.2018.2807817

[55] H. Alboqami, W. Al-Karaghouli, Y. Baeshen, I. Erkan, C. Evans, and A. Ghoneim, "Electronic word of mouth in social media: the common characteristics of retweeted and favourited marketer-generated content posted on Twitter," *Int. J. Internet Mark. Advert.*, vol. 9, no. 4, pp. 338–358,2015.
https://doi.org/10.1504/ijima.2015.072886

[56] Z. Xu, Y. Zhang, Y. Wu, and Q. Yang, "Modeling user posting behavior on social media," in *Proceedings of the 35th international ACM SIGIR conference on Research and development in information retrieval*, 2012, pp. 545–554.
https://doi.org/10.1145/2348283.2348358

[57] Q. Zhang, Y. Gong, J. Wu, H. Huang, and X. Huang, "Retweet prediction with attention-based deep neural network," in *Proceedings of the 25th ACM international on conference on information and knowledge management*, 2016, pp. 75–84.
https://doi.org/10.1145/2983323.2983809

[58] W. Zhang and S. Watts, "Online communities as communities of practice: a case study," *J. Knowl. Manag.*, 2008.

[59] F. Chen and W. H. Tan, "Marked self-exciting point process modelling of information diffusion on Twitter," *Ann. Appl. Stat.*, vol. 12, no. 4, pp. 2175–2196, 2018.
https://doi.org/10.1214/18-aoas1148

[60] M. T. Ratkovic and K. H. Eng, "Finding jumps in otherwise smooth curves: Identifying critical events in political processes," *Polit. Anal.*, vol. 18, no.1,pp.57–77,2010.
https://doi.org/10.1093/pan/mpp032

[61] K.-H. Kim, S.-T. Yun, H.-K. Kim, and J.-W. Kim, "Determination of natural backgrounds and thresholds of nitrate in South Korean groundwater using model-based statistical approaches," *J. Geochemical Explor.*, vol. 148, pp. 196–205, 2015.
https://doi.org/10.1016/j.gexplo.2014.10.001

[62] Y. Liang, K. F. Kee, and L. K. Henderson, "Towards an integrated model of strategic environmental communication: advancing theories of reactance and planned behavior in a water conservation context," *J. Appl. Commun. Res.*, vol. 46, no. 2, pp. 135–154, 2018.
https://doi.org/10.1080/00909882.2018.1437924

[63] L. Zhu, G. Yin, and W. He, "Is this opinion leader's review useful? Peripheral cues for online review helpfulness," *J. Electron. Commer. Res.*, vol.15,no.4,p.267,2014.
https://doi.org/10.1234/journal.elcres/1000789

[64] C. Xiao, B. Li, J.-Y. Zhu, W. He, M. Liu, and D. Song, "Generating adversarial examples with adversarial networks," *arXiv Prepr. arXiv1801.02610*, 2018.

[65] S. M. Mohammad and P. D. Turney, "Nrc emotion lexicon," *Natl. Res. Counc. Canada*, vol. 2, 2013.