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Hashtag Marketing and Indian brands – Sentiment Exploration

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Abstract: ***Social Media continues to impact the marketing campaign in a big way, and Indian brands are not an exception. One of the influential yet understudied tools for social media is a hashtag, which in recent times created a valuable and spellbound marketing impression. Still, less research has been done on how hashtag creates such a magnificent consumer engagement. The paper aims to answer this unfolded query by evaluating the use of the hashtag by Indian brands through sentiment analysis. There are two ways Indian brands use the hashtag – Campaign hashtag and Brand hashtag. This research is based on brand hashtags and infers quite an interesting outcome. As an experiment, we executed the hashtags for top Indian brands to identify the overall sentiment polarity of the hashtag. The outcomes were divided into two parts, wherein, in the first part, we evaluated sentiments polarities (divided into positive and negative) and computed Conversation to Engagement (C/E) Ratio and Engagement to Reach (E/R) Ratio to identify the prominence of each hashtag. In the second part of the analysis, we analyzed the responses based on demographic analysis including gender, age, interests, and occupations, which gives a clear idea of hashtag exploration. Overall, we collected 5611 texts and 154472 tokens between 01/08/2019 and 30/09/2019 from the selected brands..***

Keywords: Polarity, hashtag, Liu Hu sentiment analysis, Plutchik model..

I. INTRODUCTION

Brands are repetitively trying different channels of communication with consumers (Stathopoulou, Borel, Christodoulides, & West, 2017). With the revolutionary technological developments, social media is also considered to be the key communication channel for consumer engagement with brands (Christodoulides, 2009; Hamilton, Kaltcheva, & Rohm, 2016). Initially, it was claimed that social media will drastically increase communication between brands and consumers, the actual reach was as only 2% (Read, 2015), and, of which only 0.22% were organic (Samuel, 2017). This was a harsh setback as of fissure between claims and actuals(Page, 2012; Swani, Brown, & Milne, 2014). The hashtag was introduced with an assertion that it will duple consumer engagement (Quicksprout, 2019). The claim was found to be spot-on with 1.1 million posts with hashtags in 2016 with improved engagement. It was also witnessed that the use of hashtags further rose to 3.1 and 4.4 million in 2018 and 2019 respectively, with consumer reach and engagement almost triplicated (Influencer Marketing Hub, 2019). Fascinatingly, now almost 75% of social media posts by brands use at least 1 to 3 hashtags (O'Brien, 2017; Zhang, 2019).

Indian brands also took on social media for promoting brands and engaging consumers. Most of the Indian brands use social media for inspirational brand campaigns (SocialSamosa, 2018) for increased reach and active consumer engagement online (Economic Times, 2019). Use of hashtag is the key to getting posts, images, and videos to people, and Indian brands have used them strategically (WebguruIndia, 2019).

Some of the classical examples of Campaign hashtags in India with memorable impact are Raymonds #TheStoryRespun, Lenskarts #GandhiJiKaChashma, Vodafone's, #MakeMostOfNow campaign, Amazon India's #MomBeAGirlAgain, Olx's #OlxBreakUpChallenge, Hero Motors #ZamanaHogaFida, and Dhara oil #ZaraSaBadlaav. These campaign hashtags created a huge impact on these brands but for a short time. There are numerous papers that study the value of brand campaigns in India, effective use of brand hashtags is still unexplored.

Thus, in the present paper, we selected brand hashtags of 10 Indian brands (Bhagat, 2019; The Atlas, 2019) and evaluated its sentiment analysis. These brands are – Tata, LIC, Infosys, SBI, Mahindra, HDFC Bank, Airtel, HCL, Reliance and Wipro with brand hashtags - #tata, #lic, #infosys, #sbi, #mahindra, #hdfcbank, #airtel, #hcl, #reliance and #wipro respectively. Sentiment analysis based on polarity for these brands is evaluated using the proposed 3 step sentiment algorithm. Furthermore, these sentiments are alienated based on gender, age, interests, occupations, engagement, and reach, which gives clear insights on how Indian brands exploit hashtags.

The paper is divided into the following sections: Section 2 explains the hashtag framework we adopted for the study. Section 3 mentions the outcomes of the experiment and Section 4 gives conclusions and recommendations.

II. HASHTAG FRAMEWORK

Figure 1 elaborates on the hashtag framework adopted for the study. As specified, we collected the consumer reviews from these hashtags, conduct the preprocessing of texts, evaluate the sentiment analysis based on Liu Hu and Plutchik modeling to evaluate the polarity of sentiments, as mentioned in Figure 1 below.

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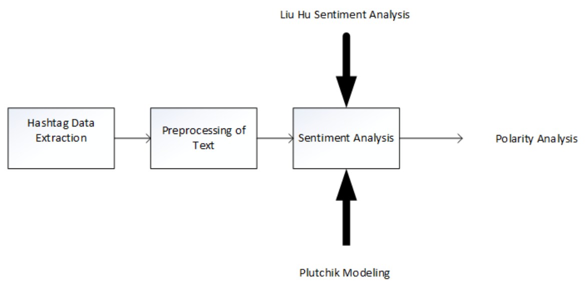

Figure 1: Proposed Hashtag Framework

Step 1: Hashtag Data Extraction

The algorithm for hashtag extraction comprises package inclusion, attaining the keys from Twitter API and then extracting the text for the hashtag. We can only extract 7 days of data from Twitter (Stephenson, 2018), so we ran the algorithm for different dates to get maximum posts.

```
# required pakacges
library(twitteR)
library(sentimentr)
consumer_key <- "waBr4IahpZ…51AqP1Mmw3Fl"
consumer_secret<-
"fumvQLQNbtYgNZqZTT3or……V9FpnCIFIbUiroKgsoMjkgO"
access_token                                     <-
"123191143-kL4e0MFc7hh…SibhHUNgpqNWZ9pKfEW8RhkCuy"
access_secret                                    <-
"HoZG076gm30SzIX….uda8cnhGUwih1Miv2ovWX9lZoEX"setu
p_twitter_oauth(consumer_key
,consumer_secret,access_token ,access_secret)
some_tweets  =  searchTwitter("#tata",    n=10000,
lang="en")
some_tweets_df <- do.call(rbind, lapply(some_tweets,
as.data.frame))
write.csv(some_tweets,            file            =
"tata.csv",row.names=FALSE, na="")
```

Step 2: Preprocessing of Text

Text collected includes various forms of data including text, emoticons, images, and videos, wherein, emoticons, images, and videos need to be removed and only intended the text to be selected for analysis. Figure 2 illustrates the 5 steps for preprocessing

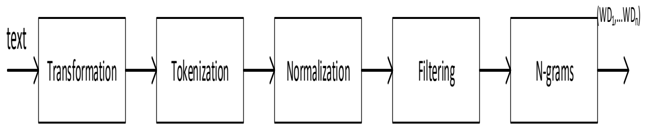

Figure 2: Preprocessing Steps

As mentioned in Figure 2, the transformation step takes texts from the hashtag and transform them into a series of words as $t_{ij} \rightarrow (W_{11}W_{12} \dots W_{1j})$, where i is a number of texts which contain j words. These j words for each text are then broken into individual words called tokens, $(W_{11}W_{12} \dots W_{1j}) \rightarrow (W_{11})(W_{12}) \dots \dots (W_{1j})$. These individual words are normalized using stemming and lemmatization. Stemming removes derivational affixes (Samir & Lahbib, 2018) and lemmatization does a morphological analysis of words (Christopher D. Manning et. al., 2008). We adopted Porter 2 Stemmer (Porter, 1980) for the step. The outcomes are mentioned as $(W_{11})(W_{12}) \dots \dots (W_{1j}) \rightarrow (w_{11}, w_{12}, \dots \dots, w_{1m})$ where, $w_{11}, w_{12}, \dots \dots, w_{1n}$ are words with similar affixes. It was also observed that some of the words from $w_{11}, w_{12}, \dots \dots, w_{1n}$ were quite common and does not take part in sentiment analysis. These words are called stop words and require filtering. This helps in overall data size and improves analysis performance (Silva & Ribeiro, 2003). The set of words after the filtering process is

$$(w_{11}, w_{12}, \dots \dots, w_{1m}) \rightarrow$$
$$(ws_{11}, ws_{12}, \dots \dots, ws_{1k})\ where\ k < m$$

The final step for preprocessing is called $n - gram$, which is a sequence of n words. For analysis, we used $n = 2$, called Bigram to get increased sentiments accuracy (Pavitra & Kalaivaani, 2015).

The final set of words are then, $(ws_{11}, ws_{12}, \dots \dots, ws_{1k}) \rightarrow (WD_{11}, WD_{13}, \dots \dots, WD_{1l})$, where $l = \frac{k}{2}$ as two words in the corpus are now combined together as $WD_1, WD_2, \dots \dots \dots WD_l$, which is the vector representation of all the bigrams.

Step 3: Sentiment Analysis

This stage gets the vectors as $WD_{11}, WD_{13}, \dots \dots \dots WD_{1l}$, wherein, each word is matched with the set of 6800 words provided by Liu Hu opinion lexicon (M. Hu & Liu, 2004; N. Hu, Bose, Koh, & Liu, 2012; X. Hu, Tang, Gao, & Liu, 2013; X. Hu, Tang, Tang, & Liu, 2013). The outcomes of this step are called Sentiment Polarity and are represented in eq. (1).

$$Polarity = \begin{Bmatrix} positive = \sum_{p \in P} weight_{positive}(p) > \sum_{n \in N} weight_{negative}(n) \\ negative = \sum_{p \in P} weight_{positive}(p) < \sum_{n \in N} weight_{negative}(n) \end{Bmatrix} \quad (1)$$

Note that from eq. (1), $p\ and\ n$ are positive and negative words based on proximity to either of them. The representation of

$$Polarity = \begin{Bmatrix} p \in (p_1, p_2, \dots \dots \dots p_n) \\ n \in (n_1, n_2, \dots \dots \dots n_m) \end{Bmatrix}$$

where $n, m \ll l$.

The intensity of each word is evaluated by determining the polarity of texts by applying the Plutchik model (Plutchik, 1982, 1988). Plutchik model identifies the polarity by evaluating the text into 8 categories - Joy, Surprise, Trust, Anticipation, Anger, Disgust, Fear, and Sadness. The positive polarity is denoted as $p \in \{Joy, Surprise, Trust, Anticipation\}$ and negative polarity is denoted as $n \in \{Anger, Disgust, Fear, Sadness\}$. The steps for sentiment exploration is mentioned in the flowchart (in Figure 3) below:

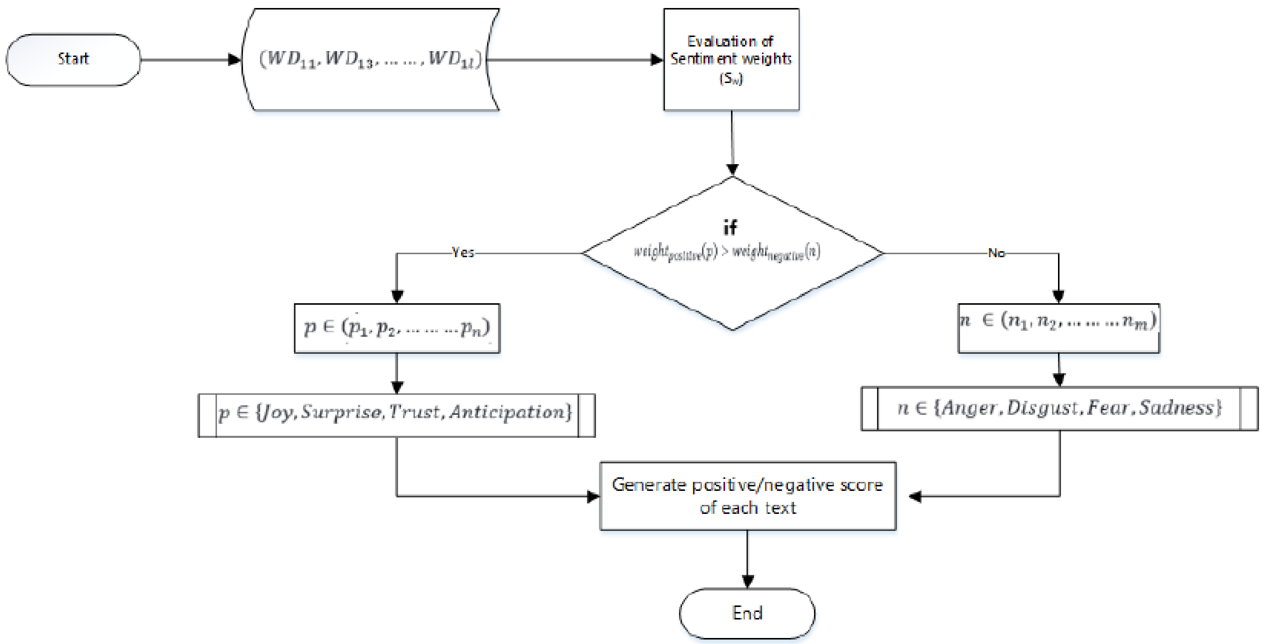

Figure 3: Sentiments Polarity Algorithm

Based on eqs (2), (3) and (4), overall calculation of positive, negative and polarity score is given in Table 2.

III. EXPERIMENT OUTCOMES

The experiment results are separated into two parts – Sentiments polarity and Demographic Analysis.

Sentiments polarity

The necessary characteristic of sentiment polarity is to analyze the text posted by consumers for understanding the opinion conveyed. Typically, we enumerate these sentiments with a positive or negative value, called polarity. Positive and Negative polarities are mentioned in eqs. (2) and (3) respectively, and based on which the Polarity Score is evaluated from eq. (4)

$$\sum_{j=1}^{m} postive_j = \sum_{j=1}^{m}\left[\prod_{j=1}^{m} Joy_j + \prod_{j=1}^{m} Surprise_j + \prod_{j=1}^{m} Trust_j + \prod_{j=1}^{m} Anticipation_j\right] \quad (2)$$

$$\sum_{j=1}^{m} negative_j = \sum_{j=1}^{m}\left[\prod_{j=1}^{m} Anger_j + \prod_{j=1}^{m} Disgust_j + \prod_{j=1}^{m} Fear_j + \prod_{j=1}^{m} Sadness_j\right] \quad (3)$$

$$Polarity\ Score = \sum_{j=1}^{m} postive_j - \sum_{j=1}^{m} negative_j \quad (4)$$

Individual polarities are mentioned in Table 1 as given below:

Table 1: Individual Polarity Collection (from Sentiment Algorithm)

			Positive Polarity				Negative Polarity			
Hashtag	Text Collected	Tokens	Joy	Surprise	Trust	Anticipation	Anger	Disgust	Fear	Sadness
#tata	852	20085	227	363	152	3	1	0	18	88
#lic	698	30965	209	177	175	5	1	3	32	96
#infosys	314	7542	128	78	65	0	0	0	5	38
#sbi	949	28153	352	242	198	11	0	3	18	125
#mahindra	311	7336	138	72	37	5	2	1	5	51
#hdfcbank	412	9069	161	71	90	2	1	0	17	70
#airtel	1264	33266	456	269	169	17	2	10	29	312
#hcl	35	645	14	7	7	0	0	1	1	5
#reliance	634	14466	225	84	197	7	1	2	46	72
#wipro	142	2945	53	28	31	3	0	0	9	18

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Table 2: Sentiments Polarity Outcomes

Hashtag	Overall positive polarity	Overall negative polarity	Polarity Score
#tata	745	107	638
#lic	566	132	434
#infosys	271	43	228
#sbi	803	146	657
#mahindra	252	59	193
#hdfcbank	324	88	236
#airtel	911	353	558
#hcl	28	7	21
#reliance	513	121	392
#wipro	115	27	88

Though Table 1 and 2 gives overall picture of adoption of hashtag by the brands, it does not give unblemished impression of the concrete adoption of brands by consumers. The adoption is evaluated using three parameters, as mentioned in eq. (5)

$$Adoption \in \{\#of\ converstions\ (C), Engagement\ (E) and\ Reach\ (R)\} \quad (5)$$

From eq. (5), we observe two important ratios, called C/E and E/R, as adoption by consumers. Table 3 gives the detailed analysis of both the ratio's. As a matter of fact, we use C/E ratio to be more than 100% $(\beta > 100\%)$ and E/R ratio to be more than 5% $(\gamma \geq 1\%)$.

Table 3: Ratios Evaluation

Hashtag	C/E Ratio	E/R Ratio
#tata	30.08	4%
#lic	66.66	2%
#infosys	57.72	0%
#sbi	29.06	1%
#mahindra	92.97	4%
#hdfcbank	189.74	1%
#airtel	96.29	3%
#hcl	174.01	1%
#reliance	130.66	0%
#wipro	166.1	0%

Demographic Analysis

The second aspect of the study is to conduct the demographic analysis. We used four parameters, namely, Gender, Age (bracket wise), Interests and Occupations respectively.

Figure 4 depicts the Gender wise acceptance of hashtags and shows an interesting outcomes of hashtag exploration.

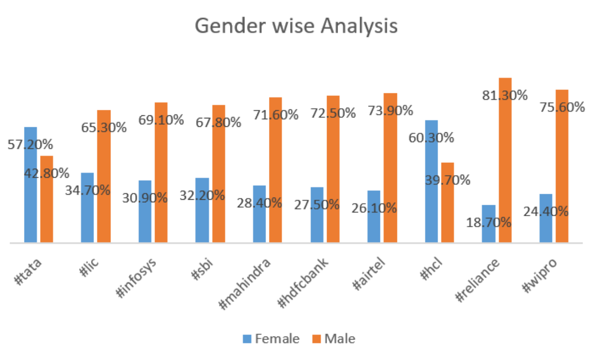

Figure 4: Gender Analysis

Figure 5 shows the age wise distribution, wherein, age bracket was divided into 5 sections as $\{18-24, 25-34, 35-44, 45-54, 54\ and\ above\}$. Surprisingly, for age bracket $54\ and\ above$, the hashtag acceptance is null.

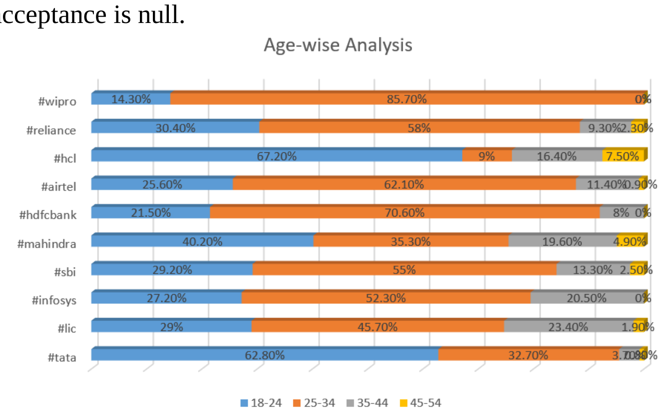

Figure 5: Age-wise Hashtag Acceptance rate

These two outcomes give an interesting strategy for the brands for positioning their contents according to gender and age wise to get maximum reach and engagement.

For social media marketing, analyzing the content based on customers' interest and occupation is the impeccable way to design and share contents, giving the attentive audience an effective way to find the content and also grouping them as dialogs. Table 4 and 5 gives the comprehensive description of brand hashtag acceptance with reference to interests and occupation from 5611 texts. We use the threshold level α, where $\alpha \geq 10\%$ for brand acceptance.

IV. CONCLUSION AND RECOMMENDATIONS

Our findings give a clear reflection of how brands use social media to leverage brand marketing and message delivery. The conclusion and recommendations are divided into 6 parts, where, we analyze the outcomes and form recommendations accordingly:

1) Out of 5611 texts collected from various social media channels used by these brands between 01/08/2019 to 30/09/2019 (these texts included the hashtags), maximum posts was done by $\#airtel\ (1264)$ and minimum by $\#hcl\ (35)$. $\#sbi, \#tata\ and\ \#reliance$ follow the numbers. However, the Overall polarity score is highest for $\#sbi(657)$ followed by $\#tata\ (638)$

2) Conversations to Engagement ratio (C/E ratio) defines the number of conversations happened to consumers getting engaged (sharing, linking and commenting) for the posts. We use $(\beta > 100\%)$ for C/E ratio adoption $(\gamma \geq 1\%)$ for E/R Ratio adoption. E/R ratio identifies the engagement of customers to total number of customers who subscribed the hashtag. $\gamma \geq 1\%$ means 1% of total number of subscribed customers are engaging in sharing, liking or commenting on the posts.

Only 4 brands $\#hdfcbank, \#hcl, \#reliance\ and\ \#wipro$ exceeded the bracket of $\beta > 100\%$, and $\#mahindra\ and\ \#airtel$ were close to 100% For E/R ratio, $\#tata\ and\ \#mahindra$ topped the chart with $\gamma = 4\%$. The E/R ratio is an alarming situation for almost all the brands as only 4% customers of overall subscribed number follow the posts.

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3) For gender demographic analysis, number of female subscribers for $\#tata\ and\ \#hcl$ are more than male subscribers. Upon analysis, we observed that for $\#tata\ and\ \#hcl$, sharing, commenting and liking for the posts are 57.20% and 60.30% by female and rest by male subscribers. For other brands, male subscribes dominate the brand subscription.
4) Age-wise demographic analysis gives 3 interesting observations:
a) For $\#tata\ and\ \#hcl$, posts sharing is more by age-bracket 18-24.
b) Secondly, for $\#wipro$, age-bracket 35-44, 45-54 and 54 or above, there is no posts sharing.
c) Thirdly, maximum posts sharing is done by age-bracket 25-34.
5) Sharing, Liking and Commenting on posts based on customers' interest gave quite a stimulating result. We observed that except for $\#wipro$, all the other customers' interest group was divided into 10 parts. For $\#wipro$, it was 8. We use the threshold level of $\alpha \geq 10\%$ for evaluation and outcomes are astounding:
a. Customers with interests in "family and parenting" share maximum posts by $\#tata$ and $\#sbi$, with $26\%\ and\ 17.30\%$ respectively.
b. Customers looking for "celebrities and entertainment news" subscribe to $\#lic$ and $\#infosys,$ with $24.5\%\ and\ 26.2\%$ respectively.
c. Customers interested in "sports" look for $\#hcl\ and\ \#wipro$ at an rate of $25\%\ and\ 24.4\%$.
d. Other interest groups are Literature/Books $(for\ \#mahindra\ 21.2\%)$, Finance $(\#hdfcbank\ 19\%)$, Music&Audio $(\#airtel\ 12.7\%)$, and General Education $(\#reliance\ 18.4\%)$.
6) Sharing, Liking and Commenting on posts based on customers' occupation also gave surprising outcomes. We were trying to divide the occupation into 10 types , however, except for $\#tata, \#sbi, \#airtel\ and\ \#reliance,$ number of occupations were less than 10. For $\#wipro$, it was only 2, with occupation Policeman and Executive manager sharing almost half of the posts. We use the threshold level of $\alpha \geq 10\%$ for evaluation and outcomes are astounding:
a. Customers with occupation "Executive Manager" share maximum posts by $\#lic, \#infosys\ and\ \#hcl$ with $17.2\%, 39.20\%\ and\ 20\%$ respectively.
b. Customers with occupation "Student" tags the maximum for brands $\#tata, \#sbi, \#airtel\ and\ \#reliance$, with $28.7\%, 36.7\%, 24.8\%\ and\ 18.6\%$ respectively.
c. Other occupations are Blogger $(for\ \#mahindra\ 28.6\%)$, Entrepreneur $(\#hdfcbank\ 28.8\%)$ and Policeman $(\#wipro\ 50\%)$

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Table 4: Hashtag interests amongst consumers

	Top Interests									
#tata	Family and Parenting	Celebrities and Entertainment News	Literature/Books	Food & Drinks	Animals	Social Media	Art	Business News	Face and Body Care	Automotive
	26.00%	16.00%	11%	10.00%	8.60%	7.30%	6.00%	5.80%	4.60%	4.40%
#lic	Celebrities and Entertainment News	Government	Global News	Legal	Food & Drinks	Music & Audio	Finance	Advertising and Marketing	Real Estate	Apparel
	24.50%	13.10%	11.60%	10.60%	10.30%	8.00%	7.70%	7.70%	5.70%	0.80%
#infosys	Celebrities and Entertainment News	Global News	Family and Parenting	Advertising and Marketing	Finance	Food & Drinks	Sports	Programming	Literature/Books	Government
	26.20%	16.70%	14.80%	10%	9.50%	5.70%	5.20%	5.20%	5.20%	1.40%
#sbi	Family and Parenting	Finance	Food & Drinks	Colleges & Universities	Travel	Celebrities and Entertainment News	Movies	Fitness & Health	General Beauty	Global News
	17.30%	13.60%	11.80%	11.10%	10.20%	10.20%	7.10%	6.40%	6.30%	6.20%
#mahindra	Literature/Books	Celebrities and Entertainment News	Global News	Automotive	Finance	Art	Sports	Music & Audio	Government	Food & Drinks
	21.20%	17.40%	13.10%	12.70%	8.50%	8.50%	4.70%	4.70%	4.70%	4.70%
#hdfcbank	Finance	Global News	Celebrities and Entertainment News	Travel	Employment	General Education	Music & Audio	Family and Parenting	Colleges & Universities	Business News
	19.00%	18.70%	18.70%	9.30%	6.60%	6.30%	6.00%	6.00%	6.00%	3.30%
#airtel	Music & Audio	Travel	Celebrities and Entertainment News	Advertising and Marketing	Colleges & Universities	Sports	Automotive	Legal	Consumer Electronics	Social Media
	12.70%	11.80%	11.80%	11.80%	11.50%	11.00%	10.40%	8.20%	7.00%	3.90%
#hcl	Sports	Legal	Global News	Food & Drinks	Fitness & Health	Family and Parenting	Consumer Electronics	Colleges & Universities	Celebrities and Entertainment News	Art
	25.00%	8.30%	8.30%	8.30%	8.30%	8.30%	8.30%	8.30%	8.30%	8.30%
#reliance	General Education	Colleges & Universities	Finance	Global News	Celebrities and Entertainment News	Government	Sports	Literature/Books	Food & Drinks	Employment
	18.40%	14.70%	12.30%	10.60%	10.60%	8.60%	8.20%	6.10%	6.10%	4.30%
#wipro	Sports	Employment	Movies	Legal	Government	Finance	Global News	Celebrities and Entertainment News		
	24.40%	24.40%	12.20%	12.20%	12.20%	12.20%	1.20%	1.20%		

Table 5: Hashtag acceptance-occupation wise

	Student	Artist/Art	Author/Writer	Teacher	Health Worker	Executive Manager	Actor	Musician	Designer	Celebrity
#tata	28.70%	18.70%	13.50%	6.80%	6.80%	6%	6%	5.20%	4.20%	4.20%
	Executive Manager	Journalist	IT Professional	Entrepreneur	Engineer	Designer	Teacher	Lawyer	Author/Writer	
#lic	17.20%	15.60%	15.60%	15.60%	15.60%	15.60%	1.60%	1.60%	1.60%	
	Executive Manager	Musician	Engineer	Actor	Student					
#infosys	39.20%	19.60%	19.60%	19.60%	2%					
	Student	Engineer	Author/Writer	Executive Manager	TV/Radio Host	Health Worker	Entrepreneur	Consultant	Customer Service	Blogger
#sbi	36.70%	12.80%	11.10%	9.30%	7.30%	7.30%	6%	3.80%	3.60%	2%
	Blogger	Trainer/Coach	Marketing	Executive Manager	Engineer	Consultant				
#mahindra	28.60%	14.30%	14.30%	14.30%	14.30%	14.30%				
	Entrepreneur	Engineer	Consultant	Aid Worker	IT Professional	Financial Analyst	Trainer/Coach	Executive Manager	Author/Writer	
#hdfcbank	28.80%	28.80%	10.60%	9.60%	9.60%	9.60%	1%	1%	1%	
	Student	Designer	Aid Worker	Marketing	Engineer	IT Professional	Financial Analyst	Executive Manager	Entrepreneur	Blogger
#airtel	24.80%	15.80%	9.30%	9.30%	9.30%	6.50%	6.20%	6.20%	6.20%	6.20%
	Executive Manager	Author/Writer	Student	Sales	Journalist	IT Professional	Entrepreneur	DJ		
#hcl	20%	20%	10%	10%	10%	10%	10%	10%		
	Student	Engineer	Journalist	Designer	Author/Writer	Aid Worker	IT Professional	Architect	Lawyer	Entrepreneur
#reliance	18.60%	18.60%	14.40%	14%	9.80%	9.30%	9.30%	4.70%	0.90%	0.50%
	Policeman	Executive Manager								
#wipro	50%	50%								

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