Abstract

Purpose-The purpose of this paper is to design organization message content strategies and analyze their information diffusion on the microblogging website Twitter.

Design- Using data from 29 brands and 9392 tweets, message strategies on twitter are classified into four strategies. Using content analysis all the tweets are classified into informational strategy, transformational strategy, interactional strategy, and promotional strategy. Additionally, the information diffusion for the developed message strategies was explored. Furthermore, message content features such as text readability features, language features, Twitter-specific features, vividness features on information diffusion are analyzed across message strategies. Additionally, the interaction between message strategies and message features was carried out.

Findings-Finding reveals that informational strategies were the dominant message strategy on Twitter. The influence of text readability features language features, Twitter-specific features, vividness features that influenced information diffusion varied across four message strategies.

Originality- This study offers a completely novel way for effectively analyzing information diffusion for brands on Twitter and can show a path to both researchers and practitioners for the development of successful social media marketing strategies.

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Analysis of content strategies of selected brand tweets and its influence on information diffusion

1. Introduction

Digital marketers across the globe can design and upload varied messages on social media. Content strategies could be analyzed in the form of message strategies as well as the message content features. Consumer responses to content strategies can be monitored by analyzing the number of “Likes”, the number of “shares”, or the number of “comments”. These responses are considered indicators of message content diffusion (De Vries *et al.,* 2012).Content strategies have been extensively studied in social media (Pletikosa Cvijikj and Michahelles, 2013;Tafesse, 2015; Kim *et al.*, 2015; Araujo *et al.*, 2015; Taecharungroj ,2017). Owing to the difference in motivations and distinctive user culture across social media platforms, the success of content strategies is dependent on the platform itself(Alhabash and McAlister, 2015). So, researchers need to study content strategies across different social media platforms. To date, most of the research on content strategies have been focused on Facebook only. However, Twitter is also extensively used by marketers, with research showing that 88 percent of businesses using Twitter for marketing purposes (Lister, 2018). Twitter can be a source of information for improving business performance(Singh *et al.,* 2019). Although Twitter facilitates information diffusion through retweets, (Jansen et al., 2009), all the messages are not equally diffused(Alboqami et al., 2015). Consequentially, brand managers ought to have a clear understanding of which content strategies cause information diffusion on Twitter. Prior research has examined the importance of message strategies which is an important feature of content strategies on Twitter(Araujo*et al.*, 2015; Taecharungroj (2016). Marketers and researchers, however, still do not fully understand which message strategies or message content features influence information diffusion on Twitter(Araujo*et al*., 2015). Earlier research works try to explain some message content features that influence information diffusion (Liu *et al.,* 2012; Hwong *et al.*, 2017; Davis *et al.*, 2019). The above authors had explored text readability features, language features, and Twitter-specific features and their influence on information diffusion. Empirical research had documented the influence of one more message feature which is vividness features and their influence on consumer responses. The influence of all these four message content features-text readability, language, Twitter-specific, vividness has not been studied across message strategies which is a valid gap that can be analyzed. By and large, all brands across industries post content that relates to product information, promotion, interaction amongst other content. But only content related to a few message strategies is diffused. So, it is necessary to analyze content diffusion factors across message strategies. Taking into consideration suggestions by social media researchers, this study is divided into three parts. In the first part of the study, message strategies are derived based on content analysis of messages. In the second part of the study, the influence of message content features such as text readability features, language features, Twitter-specific features, vividness features on information diffusion is examined across message strategies. In the third part of the study using concepts underlined by the Elaboration Likelihood Model (ELM) (Petty, Cacioppo, and Schumann, 1983) the interaction between message content strategies and message features are tested.

Additionally, this research also examines the difference in information diffusion across message strategies. This study greatly extends present literature on content strategies on Twitter, as content can be fine-tuned based on this study's recommendations to gain maximum information diffusion. In essence, this study fulfills two objectives viz., (1)Devising and exploring message strategies (2) exploring the influence of message content features-text readability features, language features, Twitter-specific features, and vividness specific features on information diffusion across message strategies, (3) analyzing the interaction between message content strategies and message features. This research can show the path to both researchers and practitioners for the development of successful social media marketing strategies.

The rest of the paper is organized as follows: section 2discusses the existing literature on message strategies, information diffusion factors, text readability features, language features, Twitter-specific features, and vividness specific features. Having discussed literature on the above areas, section 3 discusses the research methodology in detail. The results from the data analysis are then described and discussed in detail in section 4. This article is concluded with implications for managers in section 5. Limitations that provide opportunities for further research are dealt with in section 6.

2. Literature review

Earlier research had documented the importance of content strategies and consumer engagement on social media. However, most of the earlier research had focussed only on Facebook as shown below. Very few studies on content strategies and their influence on information diffusion are focused on the Twitter platform. Addressing this void, this study examines content strategies and their influence on information diffusion on Twitter. Content strategies could be operationalized in the form of message strategies as well as the message content features, so literature concerning the above areas is reviewed.

Table 1- Content strategies on social media

Authors	Social media Platform	Dependent variables	Independent variables
Araujo, Neijens, and Vliegenthart, 2015	Twitter	Retweets	Emotional cues, Informational cues
De Vries, Gensler, and Leeflang, 2012	Facebook	Likes, Comments	Vividness, Interactivity, Informational content, Entertaining content, Position, Valence of posts
Ji, Chen, Tao, and Li,2019	Facebook	Likes, Comments, Shares	Interactivity, Vividness, Emotion
Kalpana and Pillai,2013	Facebook	Likes, Comments	Content Type, Content Agility, Posting day, Content Context
Kim,Spiller and Hettche,2015	Facebook	Likes, Comments, Shares	Content Type, Media Type
Luarn, Lin, and Chiu,2015	Facebook	Likes, Comments, Shares	Content Type, Interactivity

Pletikosa and Michahelles, 2013	Facebook	Likes, Comments, Shares	Content Type, Media Type, Weekday, Posting Time
Taecharungroj (2016)	Twitter	Retweets	Information sharing, Emotion evoking, Action inducing
Tafesse and Wein, 2015	Facebook	Likes, Shares	Vividness, Interactivity, Novelty, Consistency, Content Type
This study	Twitter	Retweets	Four types of content strategies, Message features

2.1 Message strategies and information diffusion

Literature has proposed various kinds of message strategies, namely, informational or transformational messages(Laskey et al; 1989). Message strategies influence marketing effectiveness(Laskey *et al.*, 1989). Previous literature suggests many typologies are available for classifying message content. Most consist of dichotomous typologies such as informational or transformational messages (Laskey *et al.*, 1989). Informational message strategy states facts about products and services (Laskey *et al.*, 1989). The second strategy, transformational strategy, stresses the importance of the dominant psychological element present in them. In social media, scholars have analyzed the above message strategies of brands along with an interactional strategy that cultivates ongoing interactions with the customer and their impact on consumer engagement (Tafesse and Wein, 2018) on Facebook. Past research on the message strategy of brands on Twitter has been sparingly examined with only one such exclusively focussing on it(Taecharungroj, 2017). Analyzing brand content on Twitter (Taecharungroj , 2017) found that tweets can be categorized into information-sharing content, emotion-evoking content, and action inducing content. Recent research had suggested a promotion message strategy (Tafesse and Wein, 2018) as an additional message strategy to be included with the other three message strategies for devising effective message content. So keeping in view these suggestions, in this study promotion strategy is considered as an additional message strategy. Unlike Facebook, consumer responses across different message strategies on Twitter has not been discussed in any of the earlier research. In Facebook, consumer responses vary across message strategies (Luarn *et al.*, 2015; Tafesse, 2018). On a similar note, in Twitter, information diffusion-a proxy to consumer responses measured by retweets (Alboqami *et al.*, 2015; Xu and Yang, 2012) is assumed to differ across message strategies.

2.2 Information diffusion and message content features

Message content features of tweets deal with features associated with tweets that result in information diffusion. These features could be grouped into many sets of features such as text readability features, language features, Twitter-specific features, and media features. Recent research conducted by (Zhang *et al.*, 2014) indicated message content features influence information diffusion on Twitter.

2.2.1 Information diffusion and text readability features

Text readability features include many features associated with text such as length of text, number of stop words, average words per sentence, and other related features(Venturi et al., 2015). Prior research (Davis *et al.*, 2019)found that readability features such as tweet length in the short text such as tweets significantly influence information diffusion but is moderated by brand hedonism. In their research on features influencing retweeting (Xu and Yang, 2012) found that text readability features can help predict retweets**.** Research on similar lines by (Malhotra *et al.*, 2012), indicated that message length which is a key feature of text readability influences retweets. This advances the fact that text readability features can play a role in information diffusion.

2.2.2 Information diffusion and language features

Language features include parts of speech (POS)that are used to frame a sentence. Language features have been discussed to a very less extent in organizational Twitter communication. In their research on social media communication(Hwong *et al.*,2017) discussed the influence of language features on the prediction of information diffusion on Twitter. In their research(Noguti, 2016) discussed the importance of how message language features related to user engagement in different categories. This raises the question of the influence of language features on information diffusion on Twitter.

2.2.3 Information diffusion and Twitter-specific features

Twitter-specific features include hashtags, mentions, URLs associated with a message. Analyzing Twitter-specific features influencing information diffusion (Suh *et al.*, 2010)found that URLs and hashtags strongly influence it**.** Studies that are related to information diffusion suggest that the use of hashtags contributes to an increase in tweet diffusion (Lahuerta-Otero and Cordero-Gutiérrez, 2016). Applying this proposition to marketing (Davis *et al.*, 2019)found that brand hedonism moderates the influence of hashtags, at mentions on information diffusion. On similar lines, research done on the branding on Twitter indicated that Twitter-specific features such as hashtags, mentions have a significant effect on information diffusion(Lahuerta-Otero *et al*., 2018). So, it is assumed that Twitter-specific features influence information diffusion across message strategies.

2.2.4 Information diffusion and vividness specific features

Vividness refers to "the representational richness of a mediated environment as defined by its formal features; that is, how an environment presents information to the senses" (Steuer, 1992). In the context of social media, vividness is oftentimes operationalized as multimedia features in message content such as images and videos (Liu *et al.*, 2017). Empirical studies have shown the influence of vividness in Facebook brand posts (Chauhan and Pillai, 2013; Sabate et al., 2014). However, there are contradictory findings regarding their influence on audience responses. Since vividness influences audience responses it is assumed that it may influence information diffusion on Twitter.

2.2.5 Integrating message strategies and message content features

Past research related to Elaboration Likelihood Model (ELM)(Petty, Cacioppo, and Schumann, 1983)indicated that there could be a joint impact of message content strategies and message features(Goh and Chi, 2017). ELM, states that individuals process information via two separate routes: the central route that focuses on the true merit of the product or service, and the peripheral route that points to the other secondary cues such as pleasant pictures(Petty et al., 1983). Past studies in social media underline the fact that there is a higher chance that content of the message is seen as central cues whereas other features form the peripheral cues, (a). As stated by the above studies, this study proposes that message strategies are processed as central cues and other message features which are Twitter features and vividness features act as peripheral cues. Since, existing literature does not offer any empirical evidence on how interaction effect transpires in influencing information diffusion, the research question is proposed rather than stating as a hypothesis.

2.3 Research Questions and Hypothesis

To meet the goals of this study, several research questions and a hypothesis are proposed. The literature reviewed above showed the importance of message content features (text readability features, language features, Twitter-specific features, vividness specific features) in influencing information diffusion across brands across industries. However, since the influence of text readability features language features, Twitter-specific features, and vividness specific features on information diffusion and the variation of information diffusion across message strategies are unknown research questions and a hypothesis are formulated. Thus, based on the previous literature above the following research questions (RQ's) and hypothesis are presented

Hypothesis
H1:Information diffusion(retweets) varies across different message strategies (e.g., informational, transformational, interactional , promotional).

Research questions

RQ1 Which message content features influence information diffusion in an informational message strategy?

RQ2 Which message content features influence information diffusion in a transformational message strategy?

RQ3 Which message content features influence information diffusion in interactional message strategy?

RQ4 Which message content features influence information diffusion in a promotional message strategy?

RQ5 Do vividness levels and Twitter-specific features jointly influence information diffusion as measured by retweets?

3. Research Methodology

3.1 Study Overview

This study used Twitter as the microblogging platform to investigate the research questions because it is one of the most used micro-blogging websites used by companies. The unit of analysis was the individual tweet. Similar to most social media marketing strategy studies, this study used content analysis to analyze messages from sample brand Twitter pages. Content analysis is a standard method for systematically comparing the content of communications (Kolbe & Burnett, 1991). It has been used in social media content classification (Luarn et al., 2015). Content analysis was conducted to allocate tweets to informational, transformational, interactional, and promotional message content. Retweet on Twitter is considered to be an effective indicator of information diffusion (Suh *et al.*, 2010) As previously mentioned, this study used the numbers of retweets as measures of information diffusion capabilities, in line with previous studies (Alboqami *et al*., 2015; Zhang and Peng, 2015). Independent variables were text readability features, language features, and Twitter-specific features, and vividness features present in tweets. ANOVA was used to check for the difference of information diffusion across message content strategies. Quasi Poisson regression was run to check the interaction effect and influence of message features across message strategies.

3.2 Sampling procedure

All the tweets were collected from Twitter using Application Process Interface(API). Raw tweets were processed to remove stop words, punctuations, white spaces, using tm library in R software. Twitter tweets were collected for 29 brands. All messages posted were collected from the period 1/1/2016 - 14/03/2018 for 2 years and three months. Only messages posted by brands that had retweets were included in this study. A total of 9392 tweets were used for this analysis. The message strategy development was developed in three steps. In the first step, content analysis was used and all the tweets were classified into four message strategies- informational, transformational, interactional, and promotional message strategies using methodology suggested by previous studies (Tafesse and Wein, 2018). For classifying the content into four strategies keywords were used. For classifying messages into the informational strategy each of the words was constructed based on the brands used in the sample. For example, for the informational strategy "order" was used as a keyword as a food delivery brand Zomato was included in the study. For classifying messages into the transformational strategy words associated with sensory appeals such as smell, touch, feel, experience, brand elements such as awards, celebrity names were used. For classifying messages into the interactional strategy words that solicited responses from customers such as share, tag, RT, retweet were used. For classifying messages into the promotional strategy words such as discounts, cash backs, contests, puzzles were used. In the second step, each tweet was coded using content analysis and reliability of classification was assessed with the help of statistical indicators. In the third step, word clouds are drawn(Figure1, Figure2,Figure3, Figure4) showing frequent words in each strategy to further validate the above classification.
The details of the entire categorization of tweets with indicative keywords are given in the below

Table 2- Message strategies with description

Message strategy	Description of message strategy	Sample keywords
Informational	Product Attribute theme -Tweets that discuss the company offerings, brand attributes, design aspects, performance aspects, quality aspects. Knowledge theme- Tweets that provide information regarding the ways of operating the product or service	book, enjoy, flavours

Transformational	Sentimental theme -Tweets that arouse positive or negative feelings, emotions such as happiness, sadness, surprises, excitement. Brand attachment theme-Tweets that focus on establishing the identity of the brand and convey branding elements such as brand personality, brand heritage, brand logo, brand slogan, brand tie-ups, brand marketing events, celebrity marketing events, celebrity endorsements. Experiential theme- Tweets that stimulate consumers' sensory and behavioural responses such as touch, feel, odour, taste, experience.	experience, taste, ambassador, Mother's Dayd, father's day
Interactional	Consumer engagement theme- Tweets that encourage consumers to share, tweet, retweet, tag content. Customer relationship theme- Tweets that solicit consumers' responses and feedback about products and services.	like,share,retweet, rt, tag, feedback
Promotional	Nonmonetary promotions theme- Tweets that discuss a tangible or intangible gift, such as contests, gifts, bonuses presented immediately or following sometime after the purchase, or via a competition. Monetary promotions theme-Tweets attracting the consumers by offering an opportunity of price saving such as discounts, price offs, buy one get one free, cashback	cashback, offers, discounts, vouchers, deal, rebate

3.3 Coding process and reliability

A thorough review of the literature on content analysis coding procedures indicated that a coding worksheet must be prepared. Following this rule, a coding worksheet was prepared by the authors which included all the messages. Following the coding scheme suggested by Tafesse and Wein, 2018) all the messages were coded. Then, the first author coded100 tweets, and the results were compared with the coding of another researcher who does not know the purpose of the research. Any discrepancies that arose were discussed with the author. As suggested by (Krippendorff, K, 2004) pilot study of 30 tweet samples by two coders, who are unaware of the objectives of the research was conducted to check the inter-coder reliability.

The reliability of 92 percent was achieved, exceeding the acceptable level proposed by (Perreault and Leigh, 1989).

3.4 Word cloud for each message strategy

Figure1-Figure4 show the word cloud for each of the message strategy

Figure1- Word cloud for an informational strategy

The plot shows words such as Lakme, Zomato, Pepe, Lipton, Ponds which cross validates the keywords used for categorizing informational message strategy

Figure2- Word cloud for a transformational strategy

The plot shows words such as experience, brand new, stay tuned which, cross validates the keywords used for categorizing informational message strategy

Figure3- Word cloud for an interactional strategy

The plot shows words such as share, reply, rt, which, cross validates the keywords used for categorizing interactional message strategy

Figure4- Word cloud for a promotional strategy

The plot shows words such as a cashback, offers, vouchers which, cross validates the keywords used for categorizing promotional message strategy

3.5 Examples of tweets under each category

An example of text under the informational strategy

Lakmé Absolute Skin Gloss is rich in Mineral Laden Glacial Water which gives your skin a glossy sheen! https://t.co/Ix5FdBLBij.

An example of text under the transformational strategy

Bookings for the #KurkureFamilyExpress are on. To hop on board, book your ticket here: https://t.co/SfVrkDZOU2

https://t.co/h4vBUgV11g

An example of text under an interactional strategy

Loving the flow of tweets! Keep tweeting with #DrinkLiptonIceTea and visit http://t.co/15dNLXKToP. to get refreshed naturally!!

An example of text under the promotional strategy

Our first birthday giveaway is here! ? You can buy #ZomatoGold now at 20% OFF and stand a chance to win a OnePlus 6T. ? Here's to a Onederful year! ? https://t.co/Eml6gcgYx3

3.6 Model specification

Independent variables were divided into four features – text readability features, language features, Twitter-specific features, and vividness features. Text readability features included average words in the sentence, total word count, number of stop words. Language features included POS tags associated with Twitter tweets, Twitter-specific features include hashtags and mentions. To address vividness features following the methodology suggested by (Pletikosa Cvijikj and Michahelles, 2013)(vividness was coded as(0) no vividness since written in a short text, (1) low vividness for photos since these include pictorial content, (2) medium vividness for external links since these redirect the user to other websites, and (3) high vividness for videos since these offer more media richness and also include a sound. To determine the text readability features, POS tags of words, and the number of hashtags and mentions in tweets udpipe package in R software was used. The dependent variable (retweets) was highly skewed, so logarithmic transformations were used to approximate a normal distribution, consistent with extant research on engagement in social media (Davis, 2019). The transformation was Ln(1+variable), where 1 was added to prevent calculating logs of zero.

To test RQ1-RQ4 the following Quasi Poisson regression equation was formulated

In the quasi-Poisson regression model(Nelder, 2000) , the variance is calculated by multiplying the mean with a specific dispersion parameter. The quasi -Poisson model is represented below as function of μ*ij* such that

$$\mu_{ij} = exp(x_{ij}'\beta) \quad (1)$$

where xij is a vector of measured covariates, and β is a vector of parameters.
The details of the parameters and covariates are shown in below equations (2),(3), and(4)
Model1- Main effects model equation

$$\log(\vartheta) = \alpha_j + \sum_{g=0}^{3} \beta_g \left(vividness_{gj}\right) + \beta_a(\text{hashtag}) + \beta_b(\text{mention}) + \beta_c(average\ word) + \beta_{ce}(word\ count) + \beta_{de}(stopwords) + \beta_d(JJ) + \beta_e(JJR) + \beta_f(JJS) + \beta_h(NN) + \beta_k(NNP) + \beta_k(NNPS) + \beta_l(NNS) + \beta_m(PRP) + \beta_n(PRP1) + \beta_o(RB) + \beta_p(RBR) + \beta_q(RBS) + \beta_r(VB) + \beta_s(VBD) + \beta_t(VBG) + \beta_u(VBN) + \beta_{vv}(VBP) + \beta_w(VBZ) + \beta_x(WP) + \beta_{xr}(WP1) + \beta_{xt}(WRB) + \varepsilon_j \quad (2)$$

Where $\log(\vartheta)$ represented the dependent variable logretweets. The following POS tags were used as independent variables.

1. JJ adjective ‘high’
2. JJR adjective, comparative ‘higher’
3. JJS adjective, superlative ‘highest’
4. NN noun, singular ‘ticket’
5. NNS noun plural ‘tickets’
6. NNP proper noun, singular ‘India’
7. NNPS proper noun, plural ‘Indians’
8. PRP personal pronoun I, he, she

9. PRP1 possessive pronoun my, his, hers

10. RB adverb very, silently,

11. RBR adverb, comparative better

12. RBS adverb, superlative best

13. VB verb, base form share

14. VBD verb, past tense shared

15. VBG verb, gerund/present participle sharing

16. VBN verb, past participle given

17. VBP verb, sing. present, non-3d take

18. VBZ verb, 3rd person sing. present takes

19. WDT wh-determiner which

20. WP wh-pronoun who, what

21. WP1 possessive wh-pronoun whose

22 WRB wh-abverb where, when

To answer RQ5 two other Quasi Poisson regression models were created corresponding to the dependent variable lnrt. Two-way interaction terms vividness levels*hashtags and vividness levels*mentions, and three-way interaction terms vividness levels *hashtags *mentions were created and added to the model below.

Model2-Two-way interaction equation

$$\log(\vartheta) = \alpha_j + \sum_{g=0}^{3} \beta_g \left(vividness_{gj}\right) + \beta_a(\text{hashtag}) + \beta_b(\text{mention}) + \beta_{be}(\text{vividness levels} * \text{mention}) + \beta_{ge}(\text{vividness levels} * \text{hashtag}) + \beta_c(average\ word) + \beta_{ce}(word\ count) + \beta_{de}(stopwords) + \beta_d(JJ) + \beta_e(JJR) + \beta_f(JJS) + \beta_h(NN) + \beta_k(NNP) + \beta_k(NNPS) + \beta_l(NNS) + \beta_m(PRP) + \beta_n(PRP1) + \beta_o(RB) + \beta_p(RBR) + \beta_q(RBS) + \beta_r(VB) + \beta_s(VBD) + \beta_t(VBG) + \beta_u(VBN) + \beta_{vv}(VBP) + \beta_w(VBZ) + \beta_x(WP) + \beta_{xr}(WP1) + \beta_{xt}(WRB) + \varepsilon_j \quad (3)$$

Model3-Three-way interaction equation

$$\log(\vartheta) = \alpha_j + \sum_{g=0}^{3} \beta_g \left(vividness_{gj}\right) + \beta_a(\text{hashtag}) + \beta_b(\text{mention}) + \beta_{be}(\text{vividness levels} * \text{mention}) + \beta_{ge}(\text{vividness levels} * \text{hashtag}) + \beta_{he}(\text{vividness levels} * \text{hashtag} * \text{mention}) + \beta_c(average\ word) + \beta_{ce}(word\ count) + \beta_{de}(stopwords) + \beta_d(JJ) + \beta_e(JJR) + \beta_f(JJS) + \beta_h(NN) + \beta_k(NNP) + \beta_k(NNPS) + \beta_l(NNS) + \beta_m(PRP) + \beta_n(PRP1) + \beta_o(RB) + \beta_p(RBR) + \beta_q(RBS) + \beta_r(VB) + \beta_s(VBD) + \beta_t(VBG) + \beta_u(VBN) + \beta_{vv}(VBP) + \beta_w(VBZ) + \beta_x(WP) + \beta_{xr}(WP1) + \beta_{xt}(WRB) + \varepsilon_j \quad (4)$$

4. Data Analysis

To understand the overall distribution of tweets in each message strategy descriptive statistical analyses were carried out for all the four message strategies that were derived from content analysis stated above in the research methodology section. Research questions (RQ1) to (RQ4) of this study was to find out the influence of text readability features, language features, and Twitter-specific features on information diffusion across four different message strategies. To answer this set of RQ's Quasi Poisson regression was carried out.

4.1 Descriptive statistics

4.1.1 Descriptive statistics : Message strategies

Descriptive statistics related to the message strategies are presented in Table 3.

Table 3- Descriptive statistics of message strategies

Strategy	Frequency	Percentage	Retweet average
Informational	5496	59	19
Transformational	631	7	30
Interactional	729	7	29
Promotional	2536	27	18

As shown above, of the 9392 tweets, (5495;59 percent)contained informational messages ,followed by promotional(2537; 27percent), interactional (729;7percent),and promotional (631; 7percent). This shows that informational strategy messages are the dominant message strategy used by marketers.

4.1.2 Descriptive statistics : Vividness levels

The frequency statistics for the vividness levels are summarized in Table 4

Table 4- Descriptive statistics of Vividness levels

Vividness levels	N	Percentage	Retweet Average
Text	312	3	25
Photo	8340	89	17
Link	98	1	24
Video	642	7	44

Of the 9392 tweets, (8340; 89percent)contained photos ,followed by videos(642; 6percent), text(312; 3percent),and links(98; 2percent). This shows that photos are the dominant vividness medium used by marketers.

4.1.3 Cross tabulation: Vividness levels vs message strategy

Results of the Table 5 show that photo is the most dominant medium used by marketers on Twitter in each strategy(informational-90%, transformational-80%,interactional-55%,promotional-97%)

Table 5- Frequency statistics of vividness levels in each message strategy

	Informational	Transformational	Interactional	Promotional
Text	1	0	305	6
Photo	4969	502	408	2461
Link	62	2	5	29
Video	464	127	11	40
	5496	631	729	2536

4.2 Univariate regression results

The results of the ANOVA are summarized in Table 6.As suggested by earlier research in social media (Tafesse and Wien, 2018), this study used the analysis of variance (ANOVA) to test the proposed hypothesis(H1). According to H1, Information diffusion(retweets) varies across different message strategies (e.g., informational, transformational, interactional , promotional).

Table 6- ANOVA

Category	Variable	N	Mean	SD	F	Pvalue
Informational	lnrt	5495	1.942	0.583	221.8	0.00
Transformational	lnrt	631	2.022	0.635		
Interactional	lnrt	729	2.029	0.651		
Promotional	lnrt	2537	1.535	0.966		

Findings indicate that H1 was fully supported (Lnrt: $F = 221.8$, $p < 0.001$).
However, since there are unequal sample sizes robust tests for unequal sample sizes are suggested.

Table 7- Robust sample size tests

.y.	N	statistic	DFn	DFd	p	method
lnrt	9392	147.37	3	1750.687	3.78E-85	Welch ANOVA

Findings from Table 7 indicated that sample sizes have not influenced the results of ANOVA and support H1 that retweets differ across message strategies.
Post hoc test results are shown in Table 8.

Table 8- Games Howell- test

Variable	group1	group2	estimate	p.adj	p.adj.signif
lnrt	Informational	Transformational	0.079694	0.014	*
lnrt	Informational	Interactional	0.086313	0.004	**
lnrt	Informational	Promotional	-0.40722	0.0005	****
lnrt	Transformational	Interactional	0.00662	0.998	ns
lnrt	Transformational	Promotional	-0.48691	0.0005	****
lnrt	Interactional	Promotional	-0.49353	0.00005	****

Results from Table 8 indicate that there is significant difference across all message strategies pairs except for the transformational and interactional pairs

4.3 Quasi Poisson regression results: main effects model and interaction effects model

In addition to the main effects, the study explored the effect of combinations of the hashtags, mentions, and vividness levels on the number of re-Tweets. Brand messages often combine more than one feature. For example, the Tweet from Harley Davidson has a combination of hashtags and photos"Mark your calendars! The 5th #EasternHOGRally kicks off from #Indore on 17th September 2016. #HOG https://t.co/jGiZJRKc9A."

The Tweet from Ola has a combination of hashtags and link

Thrilled to partner with @airtelindia to bring a range of integrated digital offerings for millions of Indians! https://t.co/iNG0TMRsCU.

The main effects model was run with all the independent variables used in the study .Table9-13 reports the results of the regression.

4.3.1Informational message strategy

Table9 reports the results of the quasi Poisson regression results for the informational message strategy.

Table 9- Regression values for an informational message strategy

Main effect				Interaction effect			
Variables	Estimate	SE	p.value	Variables	Estimate	SE	p.value
(Intercept)	0.50	0.29	0.09	(Intercept)	0.49	0.30	0.10
avg_word	0.01***	0.00	0.00	avg_word	0.01***	0.00	0.00
word_count	-0.00*	0.00	0.07	word_count	-0.00*	0.00	0.07
stopwords	0.00***	0.00	0.00	stopwords	0.00***	0.00	0.00
Hashtag	0.03***	0.01	0.00	Hashtag	0.08***	0.03	0.02
Mention	0.00	0.01	0.91	Mention	-0.03	0.03	0.20
JJ	0.00	0.00	0.62	JJ	0.00	0.00	0.62
JJR	0.01	0.01	0.34	JJR	0.01	0.01	0.36
JJS	0.00	0.01	0.95	JJS	0.00	0.01	0.93
NN	0.00	0.00	0.87	NN	0.00	0.00	0.82
NNP	0.00**	0.00	0.02	NNP	0.00**	0.00	0.02
NNPS	0.00	0.01	0.97	NNPS	0.00	0.01	0.96
NNS	0.00	0.00	0.23	NNS	0.00	0.00	0.24
PRP	0.00	0.01	0.79	PRP	0.00	0.01	0.74
PRP1	-0.01*	0.01	0.06	PRP1	-0.01**	0.01	0.05
RB	0.00	0.00	0.95	RB	0.00	0.00	0.93
RBR	-0.02	0.02	0.46	RBR	-0.02	0.02	0.45
RBS	0.03	0.03	0.20	RBS	0.03	0.03	0.21
VB	0.00	0.00	0.58	VB	0.00	0.00	0.61
VBD	0.02**	0.01	0.03	VBD	0.02**	0.01	0.03
VBG	0.01	0.01	0.32	VBG	0.01	0.01	0.32
VBN	-0.01	0.01	0.32	VBN	-0.01	0.01	0.32
VBP	0.00	0.01	0.62	VBP	0.00	0.01	0.64
VBZ	0.00	0.01	0.82	VBZ	0.00	0.01	0.85

WP	0.04***	0.01	0.00	WP	0.04***	0.01	0.00
WP1	-0.15	0.13	0.25	WP1	-0.14	0.13	0.29
WRB	-0.02	0.01	0.24	WRB	-0.01	0.01	0.25
Photo	0.01	0.29	0.98	Photo	0.02	0.30	0.94
Link	0.11	0.29	0.70	Link	0.11	0.30	0.71
Video	0.14	0.29	0.63	Video	0.13	0.29	0.67
				Hashtag:Photo	-0.06	0.04	0.13
				Hashtag:Link	-0.05	0.09	0.60
				Mention:Photo	0.04	0.03	0.16
				Mention:Link	0.07	0.08	0.37

Note-p≤0.10.
∗∗p≤0.05.
∗∗∗ p≤0.01.

It indicates that retweets increase by using more average words in a sentence(β= 0.01, p<0.05), the number of stop words (β= 0.01, p<0.05), hashtags (β= 0.03, p<0.05), pronouns(β= 0.04, p<0.05) and verbs(β= 0.02, p<0.05, whereas the use of possessive pronouns(β= 0.01, p<0.05) decreased the number of retweets.

4.3.2 Transformational message strategy

Table10 reports the results of the quasi Poisson regression results for the transformational message strategy.

Table10 Regression values for a transformational message strategy

Main effects				Interaction effects			
Variables	Estimate	SE	p.value	Variables	Estimate	SE	p.value
(Intercept)	0.52	0.11	0.00	(Intercept)	0.52	0.11	0.00
avg_word	0.01	0.01	0.34	avg_word	0.01	0.01	0.52
word_count	0.00	0.00	0.25	word_count	0.00	0.00	0.24
stopwords	-0.01**	0.01	0.05	stopwords	-0.01**	0.01	0.03
Hashtag	0.09***	0.04	0.01	Hashtag	0.12***	0.04	0.00
Mention	-0.01	0.03	0.81	Mention	0.01	0.04	0.84
JJ	0.01*	0.01	0.07	JJ	0.02*	0.01	0.06
JJR	-0.02	0.05	0.65	JJR	-0.03	0.05	0.61
JJS	0.01	0.03	0.86	JJS	0.01	0.03	0.83
NN	0.00	0.00	0.51	NN	0.00	0.00	0.47
NNP	0.00	0.01	0.46	NNP	0.00	0.01	0.41
NNPS	-0.01	0.04	0.82	NNPS	-0.01	0.04	0.81
NNS	0.01	0.01	0.19	NNS	0.01	0.01	0.19
PRP	-0.01	0.02	0.51	PRP	-0.01	0.02	0.50
PRP1	0.00	0.02	0.96	PRP1	0.00	0.02	0.97
RB	0.01	0.01	0.22	RB	0.01	0.01	0.25
RBR	0.07	0.06	0.22	RBR	0.07	0.06	0.24

RBS	0.06	0.07	0.35	RBS	0.05	0.07	0.43
VB	0.00	0.01	0.75	VB	0.00	0.01	0.79
VBD	0.02	0.03	0.42	VBD	0.02	0.03	0.44
VBG	-0.02	0.02	0.31	VBG	-0.02	0.02	0.32
VBN	-0.02	0.02	0.49	VBN	-0.01	0.02	0.52
VBP	-0.03	0.02	0.20	VBP	-0.03	0.02	0.19
VBZ	0.00	0.02	0.82	VBZ	0.00	0.02	0.89
WP	0.05	0.05	0.32	WP	0.05	0.05	0.36
WRB	-0.01	0.05	0.83	WRB	-0.01	0.05	0.85
Link	-0.07	0.22	0.76	Link	-0.06	0.32	0.84
Video	-0.06*	0.03	0.06	Video	0.09	0.09	0.34
				Hastag:Video	-0.16	0.10	0.10
				Mention:Link	-0.04	0.45	0.93
				Mention:Video	-0.04	0.08	0.61

Note-$p \leq 0.10$.
$**p \leq 0.05$.
$***\ p \leq 0.01$.

The results showed that retweets increase by using more hashtags(β= 0.09, $p<0.05$), whereas the use of more number of video (β= 0.06, $p<0.05$) decreased the number of retweets.

4.3.3 Interactional message strategy

Table11 reports the results of the quasi Poisson regression results for the interactional message strategy.

Table11- Regression values for an interactional message strategy

	Main effect				Interaction effect		
Variables	Estimate	SE	p.value	Variables	Estimate	SE	p.value
(Intercept)	0.60	0.10	0.00	(Intercept)	0.79	0.12	0.00
avg_word	0.01*	0.01	0.07	avg_word	0.02	0.01	0.09
word_count	0.00	0.00	0.13	word_count	0.00	0.00	0.17
stopwords	-0.01	0.01	0.33	stopwords	-0.01	0.01	0.40
Hashtag	-0.05	0.03	0.10	Hashtag	-0.14	0.04	0.00
Mention	-0.14***	0.04	0.00	Mention	-0.25***	0.07	0.00
JJ	0.02**	0.01	0.02	JJ	0.02***	0.01	0.01
JJR	-0.03	0.04	0.36	JJR	-0.03	0.04	0.41
JJS	0.01	0.04	0.82	JJS	0.01	0.04	0.78
NN	0.00	0.00	0.22	NN	0.00	0.00	0.24
NNP	0.00	0.00	0.71	NNP	0.00	0.00	0.47
NNPS	-0.05	0.04	0.14	NNPS	-0.05	0.04	0.14
NNS	0.00	0.01	0.77	NNS	-0.01	0.01	0.55
PRP	0.00	0.01	0.97	PRP	0.00	0.01	0.91
PRP1	0.02	0.01	0.21	PRP1	0.02	0.01	0.20
RB	-0.02	0.01	0.09	RB	-0.02	0.01	0.05

RBR	0.02	0.05	0.73	RBR	0.04	0.05	0.42
RBS	0.17***	0.06	0.01	RBS	0.14***	0.06	0.02
VB	-0.01	0.01	0.27	VB	-0.01	0.01	0.29
VBD	0.02	0.03	0.56	VBD	0.02	0.03	0.49
VBG	0.01	0.02	0.76	VBG	0.00	0.02	0.85
VBN	0.00	0.02	0.95	VBN	0.00	0.02	0.91
VBP	0.01	0.02	0.70	VBP	0.01	0.02	0.71
VBZ	0.01	0.02	0.70	VBZ	0.01	0.02	0.70
WP	0.05	0.04	0.14	WP	0.05	0.04	0.20
WRB	0.00	0.04	0.93	WRB	0.00	0.03	0.89
Photo	0.13***	0.04	0.00	Photo	-0.16*	0.09	0.08
Link	0.01	0.14	0.94	Link	-0.25	0.31	0.42
Video	0.10	0.10	0.31	Video	-0.22	0.23	0.34
				Hashtag:Photo	0.21***	0.07	0.00
				Hashtag:Link	0.17	0.35	0.63
				Hashtag:Video	0.26	0.24	0.28
				Mention:Photo	0.14*	0.08	0.07
				Mention:Link	0.24	0.35	0.49

Note-p≤0.10.
∗∗p≤0.05.
∗∗∗ p≤0.01.

The results indicated that retweets increase by using more adjectives(β= 0.02, p<0.05), adverbs(β= 0.17, p<0.05), and photos(β= 0.13, p<0.05), whereas the use of mentions(β= 0.14, p<0.05) decreased the number of retweets. The results of the two-way interaction effect indicated that there was a strong positive interaction effect between hashtag and photo(β= 0.21, p<0.01). This suggests that when tweets with photos along with hashtags are posted by marketers using words such as retweet, rt, share, they are responded very favourably by customers.

4.3.4 Promotional message strategy

Table12 reports the results of the quasi Poisson regression results for the promotional message strategy.

Table12- Regression values for a promotional message strategy

	Main effect				Interaction effect		
Variables	Estimate	SE	p.value	Variables	Estimate	SE	p.value
(Intercept)	0.20	0.27	0.46	(Intercept)	-0.13	0.56	0.82
avg_word	-0.01	0.01	0.64	avg_word	0.00	0.01	0.71
word_count	-0.01***	0.00	0.00	word_count	-0.01***	0.00	0.00
stopwords	0.01*	0.01	0.07	stopwords	0.01*	0.01	0.06
Hashtag	0.50***	0.03	0.00	Hashtag	0.68*	0.37	0.06
Mention	-0.11***	0.03	0.00	Mention	0.08	0.51	0.88
JJ	0.01*	0.01	0.08	JJ	-0.01*	0.01	0.08
JJR	0.00	0.03	0.90	JJR	-0.01	0.03	0.84

JJS	-0.01	0.03	0.64	JJS	-0.02	0.03	0.61
NN	0.00	0.00	0.60	NN	0.00	0.00	0.59
NNP	0.01	0.00	0.24	NNP	0.01	0.00	0.24
NNPS	-0.13***	0.04	0.00	NNPS	-0.13***	0.04	0.00
NNS	0.00	0.01	0.95	NNS	0.00	0.01	0.89
PRP	0.03***	0.01	0.01	PRP	0.03***	0.01	0.01
PRP1	0.00	0.02	0.76	PRP1	0.00	0.02	0.75
RB	0.00	0.01	0.78	RB	0.00	0.01	0.80
RBR	0.02	0.05	0.72	RBR	0.02	0.05	0.70
RBS	-0.16	0.11	0.14	RBS	-0.16	0.11	0.14
VB	0.00	0.01	0.56	VB	-0.01	0.01	0.54
VBD	-0.01	0.03	0.79	VBD	-0.01	0.03	0.82
VBG	0.00	0.02	0.85	VBG	0.00	0.02	0.82
VBN	0.04*	0.02	0.06	VBN	0.04*	0.02	0.07
VBP	-0.01	0.02	0.60	VBP	-0.01	0.02	0.59
VBZ	0.00	0.02	0.98	VBZ	0.00	0.02	1.00
WP	0.02	0.04	0.72	WP	0.02	0.05	0.69
WP1	0.25	0.36	0.49	WP1	0.25	0.36	0.49
WRB	0.03	0.03	0.45	WRB	0.03	0.03	0.44
Photo	0.17	0.24	0.47	Photo	0.49	0.56	0.38
Link	-0.39	0.28	0.16	Link	-0.51	0.69	0.46
Video	0.32	0.25	0.21	Video	0.41	0.43	0.34
				Hashtag:Photo	-0.18	0.37	0.62
				Hashtag:Link	0.08	0.59	0.89
				Mention:Photo	-0.20	0.51	0.69
				Mention:Link	0.88	0.70	0.21
				Mention:Video	-0.07	0.54	0.90

Note-$p \leq 0.10$.
∗∗$p \leq 0.05$.
∗∗∗ $p \leq 0.01$.

The results indicated that retweets increase by using more hashtags($\beta = 0.5$, $p<0.05$), personal pronouns($\beta = 0.03$, $p<0.05$) and past participle verbs($\beta = 0.04$, $p<0.05$), whereas the use of more words($\beta = 0.01$, $p<0.05$), mentions($\beta = 0.12$, $p<0.05$) , proper noun plurals($\beta = 0.13$, $p<0.05$) decreased the number of retweets.

Table13 reports the results of the three-way interaction effects for the informational message strategy

Table13- Three -Way Regression values for the informational strategy

Variables	Estimate	SE	p.value
(Intercept)	0.49	0.30	0.10
avg_word	0.01***	0.00	0.00
word_count	0.00	0.00	0.07

stopwords	0.01***	0.00	0.00
Hashtag	0.07*	0.04	0.09
Mention	-0.05	0.07	0.41
JJ	0.00	0.00	0.64
JJR	0.01	0.01	0.39
JJS	0.00	0.01	0.84
NN	0.00	0.00	0.79
NNP	0.00***	0.00	0.02
NNPS	0.00	0.01	0.99
NNS	0.00	0.00	0.25
PRP	0.00	0.01	0.76
PRP1	-0.01**	0.01	0.05
RB	0.00	0.00	0.88
RBR	-0.02	0.02	0.43
RBS	0.03	0.03	0.23
VB	0.00	0.00	0.60
VBD	0.02**	0.01	0.03
VBG	0.01	0.01	0.31
VBN	-0.01	0.01	0.32
VBP	0.00	0.01	0.61
VBZ	0.00	0.01	0.88
WP	0.04***	0.01	0.00
WP1	-0.14	0.13	0.30
WRB	-0.01	0.01	0.25
Photo	0.02	0.30	0.96
Link	0.22	0.31	0.48
Video	0.13	0.29	0.66
Hastag:Photo	-0.04	0.04	0.34
Hashtag:Link	-0.19*	0.11	0.07
Mention:Photo	0.09	0.07	0.19
Mention:Link	-0.22	0.16	0.16
Hashtag:Mention	0.02	0.07	0.74
Hashtag:Mention:Photo	-0.06	0.08	0.42
Hashtag:Mention:Link	0.41***	0.18	0.02

Note-* p<0.10.
** p<0.05.
*** p<0.01.

The results of the three-way interaction effect indicated that there was a strong positive interaction effect between hashtag, mention, and link(β= 0.41, p<0.05). This suggests that when the product tweets with mentions along with hashtags containing links to websites are posted by marketers they are responded very favourably by customers.

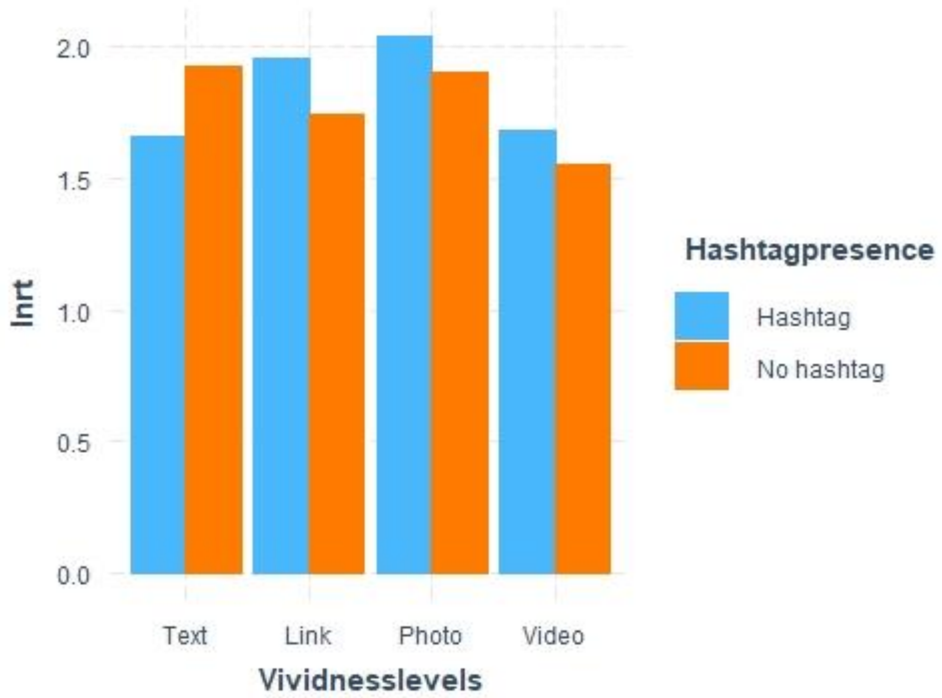

Figure5- Interaction plot between vividness levels and hashtag levels for the interactional message strategy

Table14- Strategy wise significant variables summary

Significant variables summary			
Informational	Transformational	Interactional	Promotional
avg_word	stopwords	Mention	word_count
word_count	Hashtag	JJ	NNPS
stopwords	JJ	RBS	PRP
Hashtag		Photo	
PRP1		Hashtag: Photo	
VBD			
WP			
Hashtag:Mention:Link			

Table15- Significant interaction summary table

Informational Strategy								
Variables	Text	Photo	Link	Video	Hashtag	Mention	3-way Interaction Retweet Average	Informational strategy retweet average
	0	0	1	0	1	1	**45**	19
Interactional strategy								
Variables	Text	Photo	Link	Video	Hashtag	Mention	2-way Interaction Retweet Average	Interactional strategy retweets average
	0	1	0	0	1	0	**33**	29

Note-0 indicates presence and 1 indicates an absence

5. Conclusion and Discussion

In this era of digital marketing, it is essential to gain consumer attention in media outlets especially on social media platforms such as Twitter. Consumers, in turn, have various options to look for stimulating content in social media, and marketers would not succeed without creating effective content for their consumers. Based on results from past studies, that show the importance of message strategies this study developed four message strategies. In this study, comprehensive message strategies of branded content in Twitter were developed and its information diffusion was tested. The proposed message strategies are unique in that it illustrates the applicability of these on Twitter for the first time. Message strategies were first classified into four strategies- informational, transformational, interactional, and promotional strategies. Based on the keywords and domain expertise content analysis was used and all the four strategies were developed. Because message strategies were largely applied to Facebook, the methodology proposed in this work provides a novel way of representing messages on Twitter. Thus, this study contributes to improving content marketing by organizations on Twitter. As this study is related to marketer driven content, it is focused on the analysis of factors influencing information diffusion of these content on Twitter. In addition to devising a framework for content analysis on Twitter, this study also extends the ELM framework to explain information diffusion. By, combining theoretical insights from the ELM, message strategies, Twitter features, vividness features, this study conceptualized these tweets features as distinct central cues and peripheral cues that are processed by users. Moreover, this study demonstrated through empirical evidence how these central and peripheral cues and their joint effect are related to information diffusion on Twitter. Additionally, this study adds to the existing content analysis studies on social media by integrating the concepts of ELM, message strategies, message features, and then applying the framework on a large set of real organization data. The results of this study throw further insights on the external validity of the ELM framework and message strategies topology. The findings of this study make four substantive contributions to social media literature. Firstly, results indicated that informational strategies were the dominant message strategy on Twitter. Results also indicated that photo was the dominant vividness medium used by marketers on Twitter. Secondly, it was found that there is a significant difference across message strategies in terms of information diffusion. This indicates that consumers do not see every content to be the same on Twitter. Thirdly, the influence of text readability features language features, Twitter-specific features, and vividness features that influenced retweets varied across four message strategies. Fourthly, there is a positive two way and three-way interaction effect observed across strategies. Informational message strategies were very positively influenced by language features such as proper nouns, past tense verbs, and wh pronouns. Hashtags were found to be positively influencing retweets. Interestingly, a strong three-way positive interaction was found between hashtags, mentions, and links. This indicates that messages related to product features, or brand events, celebrity events, celebrity endorsements should be included with mentions and links to either Youtube or company websites to gain maximum retweets. This was also corroborated by the fact that for tweets that included the presence of mentions, hashtags, and links the retweet average was 45 as compared to the overall message strategy average of 19. An example of a tweet in this regard is "We are excited to announce that US-based investment firm #BerkshireHathaway is now a part of our journey. Here's to a great partnership and a greater India story! @vijayshekhar ?? https://t.co/A6wBE4RBLn." Analysis of transformational message content strategies led to the conclusion that the presence of hashtags, significantly influenced retweets. So, the effect of Twitter-specific features such as hashtags is very significant in this message strategy. Further analysis indicated that retweet average with the presence of hashtags was 31 and retweet average without them was 25. So hashtags are to be included for messages in this strategy. Analysis of interactional message strategy indicated that retweets are significantly influenced by the presence of mentions, adjectives, superlative adverbs.In addition to this, the presence of photos positively influenced retweets. Over and above the individual influence of the presence of photos there is a strong positive two-way interaction effect between them and hashtags. So messages which belong to this strategy should use words such as retweet, share, rt along with hashtags, and must solicit user responses by asking them to share their photo along with the product or service. This was also substantiated by the fact that for tweets that included the presence of hashtags and photos the retweet average was 33 as compared to the overall message strategy average of 29. Over and above, the messages composed in this strategy should use more comparative adverbs such as best service, best product, etc to get maximum retweets. An analysis of promotional strategy suggested that retweets are significantly influenced by the presence of hashtags, presence of mentions, plural proper nouns, personal pronouns, and past participle verbs. Analysis indicated that nouns expressed in plural terms such as "sunglasses", "tickets", "bills" along with promotional terms such as win enhance retweets. However, for the messages in this strategy retweets increase with the increase in the number of hashtags but decreases with the increase of mentions. In addition to the individual influence of features, the study results documented joint effects between the vividness features, hashtags, and mentions of tweets on information diffusion. The results of the study corroborate earlier research on ELM indicating the influence of the interaction effect of central and peripheral cues on consumer responses. The effectiveness of social media ads may also depend on language as well. Social media advertisement(SMA) on Twitter may be processed as user tweets, and hence these findings related to language can be very helpful for designing Twitter advertisements. Marketers should proactively communicate with Twitter users and post all the four message strategies suggested in this research, that could motivate different types of users to engage with the organization. From the managerial perspective, research on content analysis from the ELM and language perspective is limited, and this work fills that gap. This study also helps practitioners by providing enough evidence to implement the suggestions in this research. Organizations that are already using Twitter can use these strategies to finetune their current content. Using the specific features suggested, for each strategy brand managers can not only analyze their own Twitter content but also understand the Twitter content of the competition and plan accordingly. It particularly enhances the understanding of the influence of the language style of content analysis and information diffusion in social media.

6. Limitations and directions for future research

Although this study provided valuable insights into features influencing information diffusion, it has a few limitations. Only some of the features influenced retweets which needs further probing. So, increasing sample sizes for each message strategy could be a way forward. The types of words used play an important role in information diffusion. Further research can explore the effect of individual words used in each message strategy which can influence information diffusion. This research was carried out using Twitter as a social media platform, so it be extended to other social media platforms such as Facebook, Instagram and the validity of the proposed message strategies and message features can be validated. Lastly, future research could also a more detailed coding scheme to yield better results during the coding phases of the research.

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