

**Evaluating marketer generated content popularity on brand fan pages- A multilevel modelling  
approach**

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## **Abstract**

Social media like Facebook has enabled brands to interact with users directly. A brand's Facebook fan page acts as a potential brand promotion platform, and it is critical for marketers to understand the subtleties of the users' interaction. This work examines the effect of marketer generated content – content type and media type, and the associated user sentiments on user interaction using sentiment mining approach and multi-level modelling. The analysis studies nearly 3000 marketer content and over 26 million user impressions across the top 25 mobile phone Facebook brand pages in India. The analysis reveals that the comments expressing user sentiments positively and recursively influence the likes and comments related to the marketers' content. Entertainment, remuneration and information based content garnered maximum likes, comments and shares respectively. The vividness of content also had differential effects on user interaction. The findings will enable mobile phone marketers to formulate an effective Facebook content strategy.

## *Keywords:*

user interaction; sentiment analysis; social media; Facebook; marketer generated content; multi-level modelling; user-generated content; likes; comments.

## **1. Introduction**

The diffusion of internet is very high today, with almost half the world population has access to internet and one-third of the total population using social media. There has been an over 80% growth in the proportion of internet and social media users in the last five years (Nextweb, 2017). With the increasing usage of internet, marketers turn to social media for sharing product information and promotions while users utilise the channel to share opinions and to network with other users.

Social media offers wider reach and direct interaction with users thereby providing a platform for marketers to engage with the user. Marketers have realised the potential of social media as a new marketing channel and are actively focusing on increasing the social media presence of their brands. Social media advertisements and brand community pages are predominantly used to increase the brand's reach among social media users. Users too participate in such social communities either to share commonly held beliefs, ideas and emotions with like-minded people or as a group of customers identifying an association with a brand (Islam and Rahman, 2017). The latter is identified as brand fan pages in social media and has been a crucial competitive advantage in enhancing brand awareness, brand trust and generating electronic word of mouth (Wang et al., 2016).

Users interacting with brand fan pages need not necessarily be customers of the product but can also include prospective customers wishing to be associated with the brand. For such prospective customers the information shared by both, the brand (i.e. marketer generated content) and other users (i.e. user-generated content), act as a source of information for purchase decisions. While brands share product-related information and promotions, users interact by sharing opinion and sentiment about the product. These are classified as marketer generated content (MGC) and user-generated content (UGC) respectively. Users who are

members of the brand's fan page are more open to receive MGC and share them with their online social community through UGC, thereby increasing the reach of brand messages. Therefore, triggering through compelling content and monitoring the UGC on social media brand pages has become a crucial part of social media content strategy.

The UGC and MGC on social media have a bidirectional reinforcement between them, as UGC is not only an outcome but also a driver of MGC (Godes and Mayzlin, 2009). Hence the objective of MGC is to publish content that stimulates user interaction. A successful MGC will have a quicker adoption by the users and aids in speeding the MGC's reach thereby increasing its popularity (Sabate et al., 2014). A popular MGC promotes the brand, influencing potential purchase decisions. Hence to enhance the acceptance of MGC by the users, marketers continuously seek to rapidly increase users interaction. However, user interaction with the MGC is a dynamic and complex process with UGC taking different forms in different platforms. The UGC is the outcome of the behavioural characteristics of the users and reflects the user's intensity to engage with the brand offerings and/or activities initiated by the marketers or users. Therefore, UGC is of key interest to marketers in order to understand the various characteristics of MGC that drives user interaction with brand fan pages.

Research have focused on understanding user interaction in social media platforms. Using netnographic analysis, the behaviour of online communities were studied to identify the customer's decision-making process (De Valck et al., 2005). The importance of user to user interactions on social media as a critical element of the marketing promotional mix was explored by Mangold and Faulds (2009). A conceptual framework has been developed based on user participation, and motivation derived out of the user activities in social media (Heinonen, 2011). Research has also been done to capture the dynamic and fluctuating nature

of user interactions on social media (Brodie et al., 2013). These research have isolated user interactions that are eventually the reactions to marketer communication. As social media is a platform where users interact with both the firm and other consumers, and user reactions are responses to marketers' content on social media, it is vital for marketers to understand the interaction with the users. Therefore, the study of the impact of user sentiments on user interaction and the influence of marketers' communication on user interaction is of great significance as it will aid marketer in understanding the dynamics of user interaction in social media.

Facebook, among all social media sites, has emerged as the largest social networking site with an average of 1.52 billion daily active users (Facebook, 2018). Facebook has more users than the total users of Twitter, WhatsApp, and Instagram (CNBC Social Media, 2014). The massive user base of Facebook is exponentially growing, and marketers recognise this avenue as an essential platform to reach their audience in a cost-effective way (Tafesse, 2015). The Social Media Marketing Industry Report<sup>1</sup> of 2018 reports that around 94% of the marketers prefer using Facebook as a key social media platform to communicate with the customers. Around 63% of the millennials follow their preferred brand on Facebook (Barnes and Correia, 2016), which approximately translates to 85%<sup>2</sup> of the total users on Facebook. The past decade has also witnessed the development of advanced technologies that have encouraged marketers to look at Facebook as an essential platform for marketing activities.

While looking at the influence of content shared by the marketer on users on Facebook, it is crucial to understand the reactions and responses of user participation and contribution in online brand communities. User to user communication, mediated by social media has loosened the control that firms held on information dissemination (Mangold, and Faulds,

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<sup>1</sup> <https://www.socialmediaexaminer.com/social-media-marketing-industry-report-2018/>

<sup>2</sup> <https://sproutsocial.com/insights/facebook-stats-for-marketers/>

2009). Therefore, to regain control marketers are keen to understand not only the user dynamics but also the responses to the marketing communication in the brand communities. Studies have investigated the impact of marketers' content on user reactions (Cvijikj et al., 2011; Shen and Bissell, 2013; Sabate et al., 2014; Tafesse, 2015) and observed it be context dependent. The content strategy depends on the sector, and the goal desired to be achieved by the brand. While studies have accounted for the sectoral characteristics, only very few studies have accounted for the brand goals. The current study intends to account for both sectoral and brand-level characteristics, and the recursive effect of UGC to study the influence of MGC on UGC.

The rest of the paper is organised as follows. First, the related works that describe the user interaction process were reviewed to develop the conceptual framework and hypotheses. Second, we explore the empirical relation between MGC and UGC with respect to mobile phone brands, which is followed by the results and discussion. Finally, we conclude by sharing the implications and limitations.

## **2. Theoretical background and hypotheses**

### *2.1 Facebook as users' online interaction tool*

The rise of social media has shifted the focus from the content that is shared by the marketer alone to the content shared by both the marketer and the user. The users are not only potential consumers but also co-creators, partnering with the firm to mould the product offering as per needs. Therefore, it is of vital importance for the marketers to engage and maintain a healthy user interaction amongst the users as it provides valuable insights. Here, the marketer content plays a pivotal role in directing user engagement on the social media platform, and marketers use various techniques to improve user interaction. The Facebook platform has been dominantly used by marketers to share posts about the brand on the official brand-owned fan

page. The posts shared are created in a way that they are interesting enough to generate user interaction on the brand's fan page. Such posts comprise the Marketer Generated Content (MGC). The fundamental attributes that define the characteristics of fan page post are its content type and the media type (Cvijikj, Spiegler and Michahelles, 2011). In order to measure user interaction on Facebook, the existing literature is reviewed to identify the appropriate metrics for the study. Facebook users engage in any post content through likes, comments, and shares from which the volume and valence are measured. Users express positive feeling about a post content by liking it or sharing it with others. They also share opinion by commenting on the post. The comments can be loaded with positive, negative, and neutral sentiments that reflect one's opinion. Thus, the user interaction on Facebook can be measured by investigating the number of likes, shares, and comments; and the sentiment of the comments can be measured by extracting the sentiments related to the comments.

The user's choice of media is understood to be primarily driven by one's desire to satisfy their motivations (Rubin, 1983). Social media being a highly interactive medium cater to an array of user motivations. Extant literature on user motivations for media usage, social media in specific, take support from Uses and Gratification theory (U&G; Katz, Haas and Gurevitch, 1973). The theory reasons that people use certain media to gratify one's need to satisfy their motivations. The current study also takes the support of U&G theory to explain user interaction on Facebook platform.

We begin by examining the influence of marketers' content as it initiates user interaction which subsequently gets driven by the shared user sentiments. We first look into the characteristics of the post shared by the marketer in a brand's fan page. We look at two characteristics of posts namely content type and media type. As different characteristics attract different levels of user interaction, we study the kind of post content and media content that triggers higher user interaction. Next, we review the influence of existing user

sentiment on subsequent interaction level, which is addressed by extracting the user sentiments using sentiment mining technique and modelling user interaction.

## *2.2 Characteristics of MGC*

### *2.2.1 Content type*

Social media content by marketers is categorised as information, entertainment, remuneration and social (Goh, Heng and Lin, 2013; Sabate et al., 2014; Luarn, Lin and Chiu, 2015). Users interact in brand fan pages to obtain substantial product-related information about the brand (Dessar, Veloutsou and Morgan-Thomas, 2015) like product description and latest product upgrades (De Vries, Gensler and Leeftang, 2012). Such information aids users in making informed purchase decisions about product alternatives. When users have a positive experience about the product through the information, they react positively to the post that has shared the information. The perception of the quality of the information posted is echoed as UGC (Islam and Rahman, 2017). Although a brand's primary motive is to share information about its product, entertaining content engages users by providing 'fun, exciting, cool, and flashy' messages that create positive user reactions (Taylor, Lewin and Strutton, 2011). The earliest study to identify information and entertainment as the content categories of the post, despite being insignificant, in explaining the user interaction was done by De Vries, Veloutsou and Morgan-Thomas (2012). However, these content categories formed the reference to classify fan page post and were later extended by other studies to accommodate more categories. Often, brand promotion activities through remunerative posts incentivise the users for participating in brand-related activities (Wood, Ray and Messinger, 2013). Shen and Bissell (2013) classified post content as events, product-related, promotion-related, entertainment and others and found that entertainment attracted the maximum number of comments. In similar lines, post content was classified with respect to the product, price, place and promotional information (Thongmak, 2015). The study found that promotional

posts significantly attracted more comments than likes and shares. The objective of social media is to encourage social participation among like-minded people. When brands share social messages, the like-minded users of the fan page interact more increasing the UGC (Daugherty, Eastin and Bright, 2008). Based on this, we classify the posts as Informative- posts that communicate information about the brand or product (Muntinga, Moorman and Smit, 2011), Social- posts that prompt the users to respond (eg: share your views) (Cvijikj and Michahelles 2013), Entertainment- posts that broadcasts non-brand or non-product related information that enables hedonic pleasure among users (eg: comedies, movies and sports-related information) , and Remuneration- posts that communicates special offers, discounts and contests (Wood, Ray and Messinger, 2013). Thus users are likely to interact with information, entertainment, remuneration and social content depending on the desire for gratifying one's need. The desire for different content types is governed by the product category. Hence, we posit:

a.) User interaction on a Facebook post varies with the content type

H1: The number of likes differs across the content types

H2: The number of comments differs across the content types

H3: The number of shares differs across the content types

### *2.2.2 Media type*

Marketer shares content containing different media formats like video, photo, link and status. Social media research observes the media type of content as content vividness. Vividness refer to the degree of sensory stimulation by the content (Steuer, 1992) and multimedia content is observed to effectually trigger multiple senses (Coyle and Thorson, 2001). For example, a video presents both audio and video stimulation while photo presents only video stimulation. Therefore, a content containing video is more vivid than a content containing a

photo. This can be explained using media richness theory that explains that the different media type trigger different senses and are learnt differently by the users (Schnotz, 2005). The online advertising research supports that highly vivid banners enhance both the click intention (Cho, 1999) and click rate (Lohtia, Donthu and Hershberger, 2003). A high vividness also enhances the user attitude on a website (Coyle and Thorson, 2001). Similar effects of vividness level were also anticipated in social media research (example: De Vries, Gensler and Leeftang, 2012; Sabate et al., 2014; Luarn, Lin and Chiu, 2015; Khan, Dongping and Wahab, 2016). Thus, advertising research in general and social media in specific suggest that higher the level of vividness, higher the user interactions. Hence, we propose:

b.) User interaction on a Facebook post is positively related to vividness of media

H4: The number of likes is positively related to vividness

H5: The number of comments is positively related to vividness

H6: The number of shares increases is positively related to vividness

### *2.3 Recursive effect of user sentiments*

While liking and sharing are abstract ways of reacting to brand post, commenting is a detailed way of communicating the feelings and emotions by the users. User comments exhibit the opinion towards a post as positive, negative or neutral. Research have shown that the exchange of positive opinions among customers enhances the brand value (Gruen, Osmonbekov and Czaplewski, 2006). When users discuss positive experiences and opinions about the brand's product on its post, it is reciprocated with similar feelings by the other users. This gets explained using affect infusion theory (Forgas, 1995) that details the user's evaluation and judgement of an object to be based on recent emotion. The brand tends to be positively evaluated by the user based on the positive affect induced on Facebook comments

and subsequently reciprocated in action. This reciprocation is reflected as UGC. Hollebeek (2011) describes this process as an 'iterative engagement processes, where user interaction on a brand post is governed by the emotions embedded in the shared post. Such sentiment can influence the information processing and interpretation of other users (Salehan and Kim, 2016), thereby governing the subsequent interaction. Studies on the impact of comment sentiments of a brand post on UGC have found that positive sentiments improved the number of likes and comments on the brand post (De Vries, Gensler and Leeflang, 2012; Khobzi and Teimourpour, 2014). As users talk positively about a post, we expect the post will be liked and shared more. Hence, we posit:

H7: Positive sentiment of a post positively influences the like count

H8: Positive sentiment of a post positively influences the share count

#### *2.4 Control Variables*

Research on information diffusion on Facebook has identified that messages transfer across 82 levels of users and is attributed to the cascading effect (Sun et al., 2009). So larger the user base, the wider is a post's reach implying higher user interaction. Few studies have accounted for the effect of the user base by controlling its influence on user interaction (Sabate et al. 2014; Swani et al., 2017; Swani and Milne, 2017). In our study, since user interaction is compared across different brands, we control the fan effect by including the number of fans of a brand fan page as a control variable. The brand's social media objective majorly drives the number of posts to be shared (Bough and Agresta, 2011) For instance, the number of posts shared by the marketer may depend on the brand's goal that may vary from seeking attention to triggering action of the user. The users' reaction may as well be affected by the frequency of post (Carboni and Maxwell, 2015; McCaskill, and Harrington, 2017). Therefore,

it is essential to control the total number of posts shared by the page during the considered period.

### **3. Method**

#### *3.1 Data Collection*

The data used for this study consisted of Facebook posts uploaded on official brand pages by marketers from the top 25 popular mobile phone brands in India. The popularity of mobile brands was determined based on the criterion of the number of fans as shared by Socialbakers (2018). The recently completed quarter (1st October 2018 to 31st December 2018) at the time of the study was chosen as the period for data collection. Out of the top 25 mobile brands, only 21 mobile brands<sup>3</sup> engaged by sharing Facebook posts and were considered for our analysis, as four brands did not have any MGC, and hence no UGC was recorded. The Facebook post data were retrieved using an application programming interface (API) – Netvizz (Rieder, 2013). The post data includes the following relevant details namely the post message, the media type of the post, and the number of likes, comments and shares.

#### *3.2 Sentiment Analysis and Post categorisation*

User sentiments were captured through the valence shared on Facebook comments made for marketer generated posts. The valence of Facebook comment was measured using sentiment analysis technique. A machine learning based analysis is suitable for formal language while a lexical-based analysis is suitable for informal language (Neri et al., 2012). Since Facebook comments comprise of informal, conversational data; a lexicon-based sentiment analysis technique is appropriate for capturing the comment sentiments. The study uses ‘sentistrength’

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<sup>3</sup> The 21 brands considered were Samsung, Oppo, HTC, Vivo, Sony, Micromax, Oneplus, MyXOLO, Motorola, Xiaomi, Panasonic, HiHonor, Gionee, Meizu, Redmi, Lenovo, Lava, Spice, Huawei, Nokia, Nubia, iTel, Tecno, Infinix, YUplaygod. Brands without MGC: MyXOLO, Gionee, Spice and YUplaygod.

(Thelwall, Buckley and Paltoglou, 2012), a popular sentiment analysis tool, that is widely used to extract comment sentiments (Jakopović and Preradović, 2013, Tang, Fang and Wang, 2014). The tool accounts for informal language usages, such as emoticons, slang words, idiom and booster words, with an inbuilt lookup table. Each word and expression is assigned a score in the range of -5 to +5 based on the pre-defined set of words in the in-built corpus. The total positive and negative scores for each comment is calculated. If the difference between the total positive and total negative is equal to zero, the comment is assigned as neutral; below zero, assigned as negative and otherwise, positive. After calculating each comment's sentiment, it is then aggregated to reflect post level sentiment. Further, the post content was categorised as information, entertainment, social and remuneration based on the broad outline shared in table 1.

INSERT TABLE 1 HERE

A standard content analysis was conducted to categorize the content types. Content analysis is defined as a scientific method to conduct a quantitative analysis of messages that is independent of the context (Neuendorf, 2002). The Facebook post were coded manually by an independent coder, without any knowledge of the research, and one of the researcher. The coding outline was briefed and asked to code about 10% (300 posts) of the total posts initially. Following which, the clarifications were provided by second researcher and asked to code all the posts. Using Perreault and Leigh (1989) formula, inter-coder reliability was approximately 0.84 and in the permissible range of 0.8-1.0. The coding discrepancies were finally sorted out by the third researcher.

The steps followed for pre-processing the Facebook data is detailed in Figure 1.

INSERT FIGURE 1 HERE

### *3.3 Descriptive Statistics*

The data comprises of 2971 Facebook posts shared by 21 mobile phone brand pages from October 2018 to December 2018, the last quarter of the year. Table 2 shows the descriptive of the post-level and page-level characteristics. The range of the number of posts shared during the considered period by the brand pages was from 26 to 298 (Average= 141.48 and SD= 76.59). We also observe that photos and Information content type being predominantly shared by the brands on their fan pages. On average a brand has shared around 141 posts during the considered period. We also check for the correlation between the number of likes, comments and shared by the posts. The post likes and post comments were significantly correlated ( $r= 0.6576$ ;  $p < 2.2e-16$ ) warranting a multivariate approach for the dependent variables. The correlation between the number of shares with likes and comments was less than 0.5.

INSERT TABLE 2 HERE

### *3.4 Model*

To test the hypotheses, we use a multivariate multilevel Poisson model (Raudenbush and Bryk, 2002) as the dependent variables are count variables. Using the multi-level models, we compare the user interaction across the 21 brands' fan pages. The posts are shared by the brand fan pages and are nested with the brand fan pages. At level 1, the user interaction gained by each post depends on unique post characteristics and the sentiment gained by the post over the considered period (level 2). The post characteristics are the outcome of different brands (level 3). Under such a scenario, we have to study the user interaction accounting the variability within brands as well as variability between brands. Further, to understand the

influence of the predictors on multiple correlated dependent variables, multivariate multilevel models are best suited. Accordingly, the variables at different levels are:

**Level 1 Dependent Variable:** The dependent variable for our model is the user interaction garnered by individual post. This will form the lowest level in the model. The user interaction is measured using the number of likes, comments and shares of each post, which are count variables.

**Level 2 Independent variables:** The characteristics of the individual post – the content type and the media type of the post and the comment sentiment are considered as the level one independent variables. Both content type and media type are categorical variables with content type taking the categories information, entertainment, remuneration and social, with information as the reference category and media type taking categories- status updates, links to other websites, image and video, with status updates as the reference category. The post sentiment is measured as the net positivity score of the comments. Net positivity is calculated as the difference between the number of positive comments and the number of negative comments (Goh, Heng and Lin, 2013).

**Level 3 Independent variables:** The brands that share the posts on their fan page.

**Control Variables:** We control for the fan base of the brand and the number of posts shared by the brand. The total number of fans following the Facebook brand page at the end of the considered period is used as a proxy for measuring the brand's fan base.

The empirical model for testing the hypotheses is shown in figure 2

INSERT FIGURE 2

The user interaction model for likes and comments is given as follows:

$$\begin{aligned}
Y = & \beta_{10}Likes_{(j)} + \beta_{20}Comments_{(j)} + \beta_{11}Likes_{(j)}Content_{(ij)} \\
& + \beta_{21}Comments_{(j)}Content_{(ij)} + \beta_{12}Likes_{(j)}Media_{(ij)} \\
& + \beta_{22}Comments_{(j)}Media_{(ij)} + \beta_{13}Likes_{(j)}(net\ postivity) \\
& + \beta_{23}Comments_{(j)}(net\ postivity) + \beta_{14}Likes_{(j)}(Fan\ base) \\
& + \beta_{24}Comments_{(j)}(Fan\ base) + \beta_{15}Likes_{(j)}(Total\ Post) \\
& + \beta_{25}Comments_{(j)}(Total\ Post) + u_{1j}Likes_{(j)}Brands \\
& + u_{2j}Comments_{(j)}Brands + e_{1j}Likes_{(j)} + e_{1j}Comments_{(j)}
\end{aligned}$$

Where,

$$\begin{aligned}
(Y_{Likes}|Likes_{(j)} = 1, Comments_{(j)} = 0) \\
= & \beta_{10} + \beta_{11}Content_{(ij)} + \beta_{12}Media_{(ij)} + \beta_{13}(net\ postivity) \\
& + \beta_{14}(Fan\ base) + \beta_{15}(Total\ Post) + u_{1j}Brands + e_{1j}
\end{aligned}$$

$$\begin{aligned}
(Y_{Comments}|Likes_{(j)} = 0, Comments_{(j)} = 1) \\
= & \beta_{20} + \beta_{21}Content_{(ij)} + \beta_{22}Media_{(ij)} + \beta_{23}(net\ postivity) \\
& + \beta_{24}(Fan\ base) + \beta_{25}(Total\ Post) + u_{2j}Brands + e_{2j}
\end{aligned}$$

And the user interaction model for shares is given as

$$\begin{aligned}
(Y_{Shares}) = & \beta_{30} + \beta_{31}Content_{(ij)} + \beta_{32}Media_{(ij)} + \beta_{33}(net\ postivity) \\
& + \beta_{34}(Fan\ base) + \beta_{35}(Total\ Post) + u_3Brands + e_3
\end{aligned}$$

Y is the combined single response variable of the number of likes and comments, and  $Y_{Shares}$  is the response variable of the number of shares. The main effects are represented as  $\beta$  coefficients; the random effects are represented as ‘u’ and the residuals as ‘e’. The first numeric subscript of the coefficients represents the response variable (1-like, 2-comment and 3- shares) and the second one the main effects variable (1- content type, 2-media type, 3- net positivity, 4 – fan base and 5 – total post). For example,  $\beta_{21}$  represents the coefficient of the main effect ‘content type’ for the response variable ‘number of comment’.

The above models were tested for its main effects of content type, media type and net positivity. We use the MCMCglmm package from R to build a multivariate multilevel

Poisson model (Hadfield, 2010). All the dependent variables, like, comment and shares were over-dispersed. To account for the over-dispersion, a post-level random effect is added to the model (Harrison, 2014). Further, to understand the variation among the brands and the differential impact of the main effects on the number of likes and comments, we fit a random effect model (with random intercept and random coefficient). Since the effect of prior on posterior estimates will be very minimal for large samples, the default priors in MCMCglmm package was used to model the main effects and random effects (Finch, Bolin and Kelley, 2016). The MCMC models (Markov chain Monte Carlo) uses Gibbs sampler using 13000 iterations with a burn-in of 3000.

## **4. Results**

### *4.1 Like and Comment*

The main effects model consists of the post characteristics, net positivity and the control measures (i.e., fan base size and the total number of posts shared by the marketer) along with the random effect - brands. The correlation between the main effect variables was less than 0.20 implying negligible concerns of multicollinearity in our model. The main effects were modelled for the number of likes and number of comments together as a bivariate Poisson regression model. Table 3 provides the estimates of the main effects and the random effects of the posterior distribution for the bivariate model.

INSERT TABLE 3 HERE

The results on content type indicate that remuneration and social content types decreased the number of likes in comparison to entertainment, while the information, remuneration and social content types increased the number of comments in comparison to entertainment. This indicates that users dither to like remuneration and social content while it is immaterial for information content. The results on media type indicate that the use of link, photo and video

increased both the number of likes and comments in comparison to status. The net positivity as well had an increasing influence on the number of likes and comments. The variance due to brands was significant both in the number of likes and comments with a mean effect of 1.93 and 1.17 respectively.

#### *4.2 Share*

We ran a univariate Poisson regression to model the main effects on the number of shares with the same control variables and random effect. Table 2 reports the means and standard deviation of the effects' posterior distribution for the univariate model. The results on content type indicate that information content increased the number of shares in comparison to entertainment content, while social content decreased the number of shares in comparison to entertainment content. This indicates that users dither to share social content. The results on media type indicate that the use of video, link and photo increased the number of shares in the given order with reference to status update. The net positivity as well had an increasing influence on the number of shares. We also find a significant variation in the number of shares among the brands with a mean effect of 2.05.

In both the models, the fan base and total post turned to be insignificant. This suggests that the number of fans and the number of posts had no significant influence on the number of likes, comments and shares. The results of the hypotheses are as given below:

Number of likes:

H1 stated that the number of likes differs across content types. The variable representing the content types namely remuneration ( $\beta_{11\text{Remu}} = -0.32$ ,  $SD = 0.22$ ) and social ( $\beta_{11\text{Social}} = -0.60$ ,  $SD = 0.22$ ) exhibited significantly different influence on post likes. Thus, H1 was supported at 0.05 level of significance.

H4 stated that increasing vividness of posts increases the number of likes. However, the variable representing low vividness (link:  $\beta_{12\text{Link}} = 1.66$ ,  $SD = 0.39$ ) gained more likes than medium vividness (photo:  $\beta_{12\text{Photo}} = 1.60$ ,  $SD = 0.33$ ). High vivid content (video:  $\beta_{12\text{Video}} = 1.01$ ,  $SD = 0.33$ ) garnered lesser likes than low and medium vivid content. This is contrary to our hypothesis. Thus, H4 was not supported, as the positive influence of vividness was significant but observed to be in the order of low, medium and high.

H7 stated that an increase in the positive sentiment of the post increased the number of likes. In lines with our hypothesis, the effect of net positivity was supported at 0.05 level of significance and increased the number of likes ( $\beta_{13} = 0.01$ ,  $SD = 0.00$ ).

Number of comments:

H2 stated that the number of comments differ across content types. The variables representing remuneration ( $\beta_{21\text{Remu}} = 0.67$ ,  $SD = 0.16$ ), information ( $\beta_{21\text{Inform}} = 0.34$ ,  $SD = 0.14$ ) and social ( $\beta_{21\text{Social}} = 0.20$ ,  $SD = 0.17$ ), content exhibited significantly different influence on post comments. Thus, H2 was supported at 0.05 level of significance.

H5 stated that increasing vividness of posts increases the number of comments. The variable representing medium vividness (photo:  $\beta_{22\text{Photo}} = 0.46$ ,  $SD = 0.27$ ) gained more comments than low vividness (link:  $\beta_{22\text{Link}} = 0.39$ ,  $SD = 0.32$ ). However, high vivid content (video:  $\beta_{22\text{Video}} = 0.27$ ,  $SD = 0.28$ ) garnered lesser comments than medium and low vivid content. This is contrary to our hypothesis. Thus, H5 was not supported, as the positive influence of vividness was significant but observed to be in the order of medium, low and high.

Number of shares:

H3 stated that the number of shares differs across content types. The variables representing information ( $\beta_{31\text{Inform}} = 0.14$ ,  $SD = 0.15$ ) and social ( $\beta_{31\text{Social}} = -0.27$ ,  $SD = 0.18$ ), content

exhibited significantly different influence on post shares. Thus, H3 was supported at 0.05 level of significance.

H6 stated that increasing vividness of posts increases the number of shares. The variable representing high vividness (video:  $\beta_{32\text{Video}}=1.43$ ,  $SD =0.30$ ) gained more shares than low vividness (link:  $\beta_{32\text{Link}}=1.25$ ,  $SD =0.35$ ). However, medium vivid content (photo:  $\beta_{32\text{Photo}}=1.04$ ,  $SD = 0.30$ ) garnered lesser shares than low vivid content. This is contrary to our hypothesis. Thus, H6 was also not supported, as the positive influence of vividness was significant but observed to be in the order of high, low and medium.

H8 stated that an increase in the positive sentiment of the post increased the number of shares. From the model, we find that H8 is supported at 0.05 level of significance with the number of shares ( $\beta_{33}=0.01$   $SD =0.00$ ) increasing with net positivity.

#### *4.3 Other Analysis*

We also check the robustness of the bivariate model by developing two separate univariate Poisson regression models for post likes and comments. If the results of the univariate model are closely similar to that of the bivariate model, we can safely assume the model produces consistent results (Swani et al., 2017). Accordingly, we find the results of the univariate models (Table 4) supporting H1, H2, H3, H7 and H8. Also, we find a considerable reduction in the proportion of variance unexplained by the main effects in the bivariate model than the univariate models.

INSERT TABLE 4 HERE

### **5. Discussion**

We examined the popularity of the MGC on brands' fan page by exploring the underlying mechanism in which user interaction happens on Facebook. By analysing 2971 unique posts

across 21 brands' fan page, we investigate the MGC characteristics and the effect of user sentiments that encourages users interaction - measured by number likes, comments and shares, which thereby increases the reach of MGC. The study used multi-level modelling to account the variation across different fan pages in modelling user interaction and accounted for differences in FB brand page attributes namely the brand and the number of fans.

The liking, commenting and sharing on brand fan pages are triggered by the gratification of different user motivations. Considering the common motivation that influences the behaviour, we found a high correlation between the number of likes and the number of comments of a post. This suggests that user interaction does possess high social contagion effect triggering further interaction among the users (Aral and Walker, 2011). More specifically, our results show that users are more likely to react by 'liking' a post than by 'commenting'. The study distinguished the activities and built two models to accommodate the distinction of liking and commenting from sharing as employed in few previous studies. The results of the model show that the use of social content or remuneration content garners a lower number of likes than comments. This can be explained using the composition-based behaviours related to comments as the remunerative and social content may trigger a deeper level of interaction with the brands (Muntinga, Moorman and Smit, 2011; Luarn, Lin and Chiu, 2015).

Furthermore, the results show that information content garners increased comment. This can be attributed to the information-seeking nature of users (Muntinga, Moorman and Smit, 2011). Thus, remuneration information and social content are potential means to trigger user comments. Entertainment content garners the maximum likes and can be explained through the uses and gratification theory. Wherein, the users' motivation for seeking entertainment may possibly exhibit an increased drive for users to like entertaining content. Results also showed that information content gained the maximum shares, reflecting the users' need for

self-enhancement (Berger, 2014) and satiating the information exchange behaviour of users (Khan, Dongping and Wahab, 2016).

Next, we find that the use of vividness in the posts as link, photo and video enhance the liking, commenting and sharing of post by users. Contrast to our hypotheses (H4, H5 and H6) a high vivid content in the form of video did not garner higher likes and comments than photo or link. This can be possibly attributed to the longer view time of videos over photos (De Vries, Gensler and Leeflang, 2012; Luarn, Lin and Chiu, 2015). However, a high vivid content garnered maximum shares, in lines with our hypothesis. This can be explained using the inherent differences in liking, commenting and sharing behaviour, where sharing enunciates the highest commitment level as it forms a part of self-representation (Kim and Yang, 2017). For likes, a low vivid content containing links garnered the maximum likes and photos that represent medium vividness garnered the maximum comments. Since liking is an affectively driven and commenting is a cognitively driven behaviour, the user may possibly react in different ways depending on the vividness level (Kim and Yang, 2017; Swani et al., 2017).

The positive sentiment is observed to positively influence the liking, commenting and sharing behaviour of the user. Since users' perception about an object is influenced by the recent opinion surrounding the object (Forgas, 1995), we believe the increased user reaction is probably due to the positive opinions commented on the brand's post.

## **6. Conclusion**

Social media has proven to be an efficient marketing channel as it allows users to interact with brands. Hence firms' presence on Facebook should not be a mere existence rather an active involvement in sharing brand posts that invite significant user interaction. In this line, the study has aided to understand the influence of marketer generated content by classifying

the content as information, remuneration, social and entertainment as employed in select studies (De Vries, Gensler and Leeftang, 2012; Luarn, Lin and Chiu, 2015). In addition, the study also accounted for the recursive effect of user sentiments on user-generated content as observed in scarce literature (De Vries, Gensler and Leeftang, 2012; Khobzi and Teimourpour, 2014). Thus, the study pragmatically backs the significance of ascertaining the content type and media type of content to be shared by marketers for effective user interaction. For example, the mobile phone marketer's desire to encourage user comments should share entertainment content to reinforce pleasurable user experiences, a low level of vividness garner maximum likes etc. Further, the study also supports the need to preserve the positive sentiment on social media to enhance user interaction.

Although the study delivered the desired result, it has certain limitations. The study is restricted only to Facebook platform, and future research could extend this to other social media platforms such as Twitter and LinkedIn. The user interaction is context specific and driven by the sectoral characteristics. The present study limits to mobile phone category and cannot be generalised to other product categories. The sample data is specific to brands in India to control the influence of any cultural dimension. It would be interesting to conduct a cross-cultural study to appreciate the differences in user interactions with MGC across culture. A complementary study to our research would be to explore the influence of user-generated content on brand performance (say sales, brand equity etc.). Thus the research intended to study the influence of marketer generated content and the recursive effect of comment sentiment on Facebook, for which the work provides a definitive treatment.

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| Table 1: Outline on content types |               |                                                                                                       |
|-----------------------------------|---------------|-------------------------------------------------------------------------------------------------------|
| No                                | Content type  | Description                                                                                           |
| 1                                 | Information   | Contains brand related details like feature, sale, promotional activities etc.                        |
| 2                                 | Entertainment | Content beyond brand like humorous vieos, teasers, slogans or motivational quotes                     |
| 3                                 | Social        | Questions or statements intended to elicit interaction and encourage user participation               |
| 4                                 | Remuneration  | Information on direct or indirect user benefits like prizes through contest, discount, giveaways etc. |

Table 2: Post Characteristics (Level 1) and Fan Page Characteristics (Level 2)

| Post Characteristics      |                                          | Count   | Percentage |
|---------------------------|------------------------------------------|---------|------------|
| Media Type                | link                                     | 149     | 5%         |
|                           | photo                                    | 1666    | 59%        |
|                           | status                                   | 66      | 5%         |
|                           | video                                    | 1090    | 33%        |
| Content Type              | Entertainment                            | 223     | 8%         |
|                           | Information                              | 1989    | 72%        |
|                           | Remuneration                             | 409     | 4%         |
|                           | Social                                   | 350     | 4%         |
| Number of Brand Fan pages |                                          | 21      |            |
|                           | Average number of likes                  | 8623    |            |
|                           | Average number of comments               | 103     |            |
|                           | Average number of shares                 | 109     |            |
|                           | Average Fan base                         | 3464011 |            |
|                           | Average number of Posts shared by brands | 141     |            |

Table 3. Multilevel Poisson regression results

|                           | Bivariate |      | Univariate |      |          |      |
|---------------------------|-----------|------|------------|------|----------|------|
|                           | Likes     |      | Comments   |      | Shares   |      |
| Main effects              | Estimate  | SD   | Estimate   | SD   | Estimate | SD   |
| Intercept                 | 5.05*     | 0.79 | 2.42*      | 1.60 | 1.38*    | 0.75 |
| Net_Postivity             | 0.01*     | 0.00 | 0.01*      | 0.00 | 0.01*    | 0.00 |
| Content type Information  | 0.15      | 0.18 | 0.34*      | 0.26 | 0.14*    | 0.15 |
| Content type Remuneration | -0.32*    | 0.22 | 0.67*      | 0.45 | -0.02    | 0.18 |
| Content type Social       | -0.60*    | 0.22 | 0.20*      | 0.21 | -0.27*   | 0.18 |
| Media type Link           | 1.66*     | 0.39 | 0.39*      | 0.39 | 1.25*    | 0.35 |
| Media type Photo          | 1.60*     | 0.33 | 0.46*      | 0.40 | 1.04*    | 0.30 |
| Media type Video          | 1.01*     | 0.33 | 0.27*      | 0.30 | 1.43*    | 0.30 |
| Fan Base                  | 0.32      | 0.70 | 0.32       | 0.51 | 0.33     | 0.74 |
| Total posts shared        | 0.25      | 0.60 | 0.14       | 0.37 | 0.19     | 0.59 |
| Random effects: Brand     | 1.93*     |      | 1.17*      |      | 2.05     |      |
| Residuals                 | 1.54      |      | 0.75       |      | 0.16     |      |
| Proportion of variance    | 0.56      |      | 0.61       |      | 0.93     |      |

Note: \* $p < .05$

Table 4. Univariate Poisson regression results

| Main effects              | Likes    |      | Comments |      |
|---------------------------|----------|------|----------|------|
|                           | Estimate | SD   | Estimate | SD   |
| Intercept                 | 5.06*    | 0.77 | 2.38*    | 0.58 |
| Net_Postivity             | 0.01*    | 0.00 | 0.01*    | 0.00 |
| Content type Information  | 0.16*    | 0.19 | 0.34*    | 0.15 |
| Content type Remuneration | -0.32*   | 0.21 | 0.66*    | 0.17 |
| Content type Social       | -0.59*   | 0.22 | 0.21*    | 0.17 |
| Media type Link           | 1.65*    | 0.41 | 0.43*    | 0.33 |
| Media type Photo          | 1.59*    | 0.33 | 0.51*    | 0.27 |
| Media type Video          | 0.99*    | 0.33 | 0.31*    | 0.27 |
| Fan Base                  | 0.32     | 0.71 | 0.30     | 0.57 |
| Total posts shared        | 0.24     | 0.55 | 0.15     | 0.47 |
| Random effects: Brand     | 1.80*    |      | 1.13*    |      |
| Residuals                 | 1.23     |      | 0.65     |      |
| Proportion of variance    | 0.59     |      | 0.64     |      |

Note: \* $p < .05$

Figure 1: Data Pre-processing

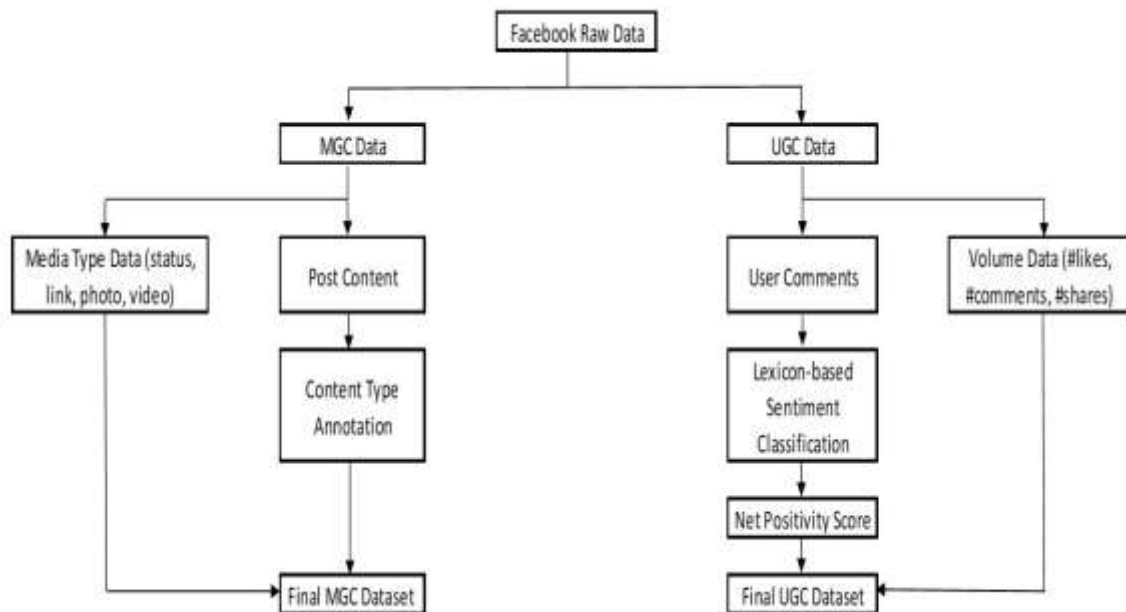


Figure 2: Empirical model evaluating marketer generated content popularity

