MODELING MGC STRATEGIES UNDER EXTREME NEGATIVE UGC

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ABSTRACT

The impact of user-generated content (UGC), especially extreme negative UGC (EN_UGC) on firms is well recognized. Moreover, insightful qualitative marketer-generated content (MGC) strategies have been proposed to respond to negative UGC. However, few quantitative and analytical modeling studies have been conducted to explore the effectiveness of each proposed strategies under different scenarios to counteract EN_UGC. This research aims to explore optimal MGC strategies for firms to handle EN_UGC by proposing an EN_UGC propagation model based on MGC and EN_UGC interaction. We provide the runaway mode and effective mode in handling EN_UGC. Our results show that in runaway mode, MGC does not affect the propagation of EN_UGC, and the optimal MGC strategy is to do nothing. However, in effective mode, the effect strength of MGC on EN_UGC is the most important key factor in defending against EN_UGC propagation, followed by the input rate of the subgroup where users accept and repost MGC. Based on our model, we also explain why MGC strategies such as deleting post and employing paid posters are helpless in EN_UGC's management. Overall, the findings in this research offer some unique implications for UGC management.

Keywords: User generated content; Marketer generated content; Runaway mode; Effective mode; Social media

1. Introduction

The popularity and user-friendliness of social media has witnessed a dramatic increase in online user engagement with organizations [Susarla et al. 2012]. This engagement generates massive amount of user generated content (UGC). Firms have capitalized on the positive impact of UGC on brand value and revenue generation. However, users also say nasty things about firms and their brands. Thus, UGC can be negative or even extreme negative which has detrimental effect on firms and their brand value.

For example, in 2010, Nestlé, the world's biggest food manufacturer, had to face the tough criticism storm from social media. On March 17, 2010, Greenpeace as one of the largest environmental groups launched a "Have a break;

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have a Kit Kat" video on YouTube attacking Nestlé's Kit Kat brand. Greenpeace had found that Nestlé was sourcing palm oil from Sinar Mas, an Indonesian supplier that Greenpeace claimed was acting unsustainably. Millions of people watched the grisly video and posted angry messages on Nestlé's Facebook page. In order to counteract the negative effect, Nestlé attempted to use censorship to refrain the negative UGC and forced Greenpeace to withdraw the video from YouTube. However, the withdrawal did not stop the spreading of the message in social media. The withdrawal even made the situation worse. Main stream media also joined social media force. The censorship along with hostile and sarcastic message of Nestlé toward consumers severely damaged the brand image of Nestlé [Magee 2010].This example illustrates if firms do not manage negative UGC appropriately, negative UGC can be detrimental.

However, if firms can formulate sound social media strategies and take proper actions to take advantage of marketer generated content (MGC), they can mitigate the potential damage from UGC. Unfortunately, limited research especially quantitative and analytical modeling studies has been conducted on how firms should deploy MGC strategies to effectively respond to extreme negative UGC (EN_UGC) [Goh et al. 2013; Thomas et al. 2012; Ye et al. 2011]. Hence, it is worthwhile to identify the dynamic interaction mechanism between EN_UGC and MGC, and offer optimal MGC strategies to mitigate the damage from EN_UGC. We attempt to address the research gap in this research. Our contribution lies in that we propose the mathematical model and explore the conditions under which firms' MGC strategies for dealing with EN_UGC can be effective.

The rest of the paper is arranged as the following. In Section 2, we provide literature review. In Section 3, we define major terms in this study. In Section 4, we build the model and explore the stability of the equilibrium, present quantitative MGC strategies for managing EN_UGC in runaway mode and effective mode respectively. In last section, we conclude the paper with the discussion of major findings, limitations and future research.

2. Literature Review

2.1. Managerial strategies for negative UGC

To combat the negative UGC, firms usually can exploit two strategies: censoring and online managerial response [Ye et al. 2011]. Censoring is a common practice used by marketers to manage negative UGC. Several case studies investigated the effectiveness of censoring on negative UGC. For example, Modine [2008] reported that Amazon.uk removed a vast majority of negative reviews on *Crysis Warhead*, a PC game produced by Electronic Arts. The removal increased the review rating of the game from 1.5 to 3. NewEgg.com has an eight-person team dedicated to monitoring consumer reviews especially negative UGC [Kawakami 2005]. However, the effectiveness of censoring is questionable. First, censoring can be easily detected by consumers [Modine 2008]. Second, evidences suggest that censorship could hurt marketers' reputation and brand value [Awad & Zhang 2007; Thomas et al. 2012].

Online managerial response is a new research field in recent years and has attracted a lot of research interests. However, prior research focuses on the qualitative managerial strategies for marketers to respond to negative UGC. For example, Shen et al. [2010] presented five response strategies that marketers may adopt: confession, excuse, justification, denial and silence. Thomas et al. [2012] unpacked options for marketers to dealing with unexpected negative UGC: delay, respond, partner, legal action, and censorship. Xia [2013] proposed two responses to consumer criticism: defensive response and vulnerable response, and found that vulnerable response leads to positive behavioral responses from consumers and it does not damage consumers' perceptions of product quality. Gu and Ye [2014] measured the impact of management responses on customer satisfaction using data from a major online travel agency in China. They found that online managerial response is highly effective for low satisfaction consumers. However, it has limited influence on other consumers. Our work differs from previous research in that we built a mathematical model to quantitatively analyze MGC strategies under different scenarios to overcome the negative UGC in social media.

2.2. Information propagation in social media

Information propagation in social media has drawn much attention from the networking, viral marketing and data mining research communities. Epidemic model is one of the most representative models to extract information propagation. For example, Nguyen and Shinoda [2007] applied the classical epidemiological model with an in-depth exploration of the average number of newly infected network nodes. Saito et al. [2012] used a SIS (susceptible, infected and susceptible) epidemic model to characterize the process of information diffusion over social networks. They found that influential nodes play a disproportional role in information diffusion.

Although epidemic model is one of theoretical bases for this research, there are still some weaknesses in the prior information propagation models. First, prior studies consider the interaction networks as static entities. The static view of interaction hides the fact that once negative UGC occurs, marketers will participate and release MGC to suppress the effect of negative UGC on firm value, reputation and brands. Second, most prior models focus on describing the information propagation and yet rarely involve the intervention from other subjects. Based on prior research, we offer an interaction model to highlight strategies firms can adopt to make the UGC information propagation under control.

2.3. Opinion interaction in social media

Opinion interaction is the connection among individuals who have a positive or negative opinion that can influence each other's judgments and attitudes. Acemoglu et al. [2010] investigated a model in which agents meet and adopt the average of their pre-meeting opinions. They found that powerful agents can influence the magnitude of the opinions of others but may not change the direction of others' opinions. Song et al. [2007] used a continuous time markov chain to rank the influence of users and to determine the correlation between the adoption of an idea for pairs of users. Crandall et al. [2008] modelled the interactions between social influence and selection using data from online communities. They found that the relative value of similarity and social influence is apparent in predicting future behavior. Susarla et al. [2012] found that social interactions are influential not only in determining which video become successful but also on the magnitude of the impact. Goh et al. [2013] integrated qualitative user-marketer interaction content data at the individual consumer level from a fan brand community on Facebook with consumer transactions data to quantify the relative impact of community content from consumers and marketers on consumers' apparel purchase expenditures. They found that MGC has relatively weak influences on consumers compared to UGC influence.

Though prior research generates insightful observations, most studies orient towards a single piece of information and do not capture the effects of multiple pieces of information on user behavior changes. Generally speaking, there are multiple pieces of information coexisting in the real-world and these pieces of information spread through social networks simultaneously. Moreover, these studies focus on the social influence from similar users, and do not investigate how users in social media interact with the content from fully heterogeneous sources such as UGC and MGC. This study contributes to closing this gap by proposing a theoretical model for analyzing the interaction between UGC and MGC.

3. Major Terms and Definitions

3.1. Social media

In line with prior research, social media in this research is defined as a group of Internet-based applications that build on the ideological and technological foundations of Web 2.0, which allows the creation and exchange of user generated content [Kaplan & Haenlein 2010]

3.2. User generated content (UGC)

UGC refers to a variety of media content available in a range of modern communications technologies such as blogs, and other social media sites such as Facebook and Twitter. UGC is created by goal-oriented yet loosely coordinated participants, who interact to create a product (or service) of economic value, which they make available to contributors and non-contributors alike. Yu and Hatzivassiloglou [2003] proposed a model that divides the polarity of UGC into positive, negative and neutral. As for negative UGC, it can be classified as extreme negative UGC (hereafter *EN_UGC*) and normal negative UGC (hereafter *NN_UGC*) according to their different characteristics. EN_UGC is unexpected negative UGC for a firm, which has a high possibility to cause wide negative social influence.

NN_UGC such as online review usually refers to consumers' negative online evaluation on attributes/features of a special product/service (e.g., quality, function) of a firm. NN_UGC is posted in online reviews platforms [Liu 2010]. Generally speaking, NN_UGC won't cause unexpected negative influence in firm value in a short period of time, although some studies have found that NN_UGC has negative impact on the sales of a firm [Chatterjee 2001; Chevalier & Mayzlin 2006]. Table 1 shows that the differences between EN_UGC and NN_UGC. In this paper, we focus on EN_UGC.

Table 1: Comparison with EN_UGC and NN_UGC

	EN_UGC	NN_UGC
Platform	Social network e.g., Facebook, YouTube, microblog, douban.com	Online reviews platform e.g.,Tmall.com, jingdong.com, tripadvisor.com, Amazon.com
Content	Social responsibility, environmental awareness, worker's right, product safety, etc.	quality, function, experience, etc.
Risk	Very high	Relative low
Consequence	Unexpected and destructive consequence for a firm suddenly	Expected and moderate consequence for a firm gradually
Case	Nestlé case [Thomas et al. 2012] United breaks guitar [Deighton & Leora 2010]	Amazon.uk case [Modine 2008] NewEgg.com [Kawakami 2005]

3.3. Marketer generated content (MGC)

In contrast with UGC, MGC refers to the Internet content produced by a firm officially in social media outlets. The purpose to release MGC is to response to EN_UGC. In order to minimize the negative influence, the firm needs to decide whether to deny the EN_UGC or admit it. If admitting, it is important to determine the timing for releasing MGC, the information quantity of MGC and the interval duration between the last MGC releasing and subsequent MGC releasing. Proper MGC strategies can minimize the reputation risks from EN_UGC.

3.4. Deviation distance between EN_UGC and the true information

We assume that firms have the ability to get the true information of the events involved in the EN_UGC, while consumers are relatively in shortage of the true information. For EN_UGC, there always exists a bias against the truth (hereafter deviation distance) which can be perceived by firms. We represent the mentioned aspects of a EN_UGC using a vector $\boldsymbol{c_U}$, and simultaneously using a vector $\boldsymbol{c_R}$ denoting true information. Thus, deviation distance is measured as

$$d_{UR} = dis(\boldsymbol{c_U}, \boldsymbol{c_R}),$$

where $\boldsymbol{c_U}$ and $\boldsymbol{c_R}$ are the respective characteristic vectors of EN_UGC and true information, $dis(.)$ is a distance function, and $d_{UR} > 0$. Hence, the higher the value of d_{UR} is, the less information similarity between UGC and true information exists. For firms, the deviation distance usually has a threshold θ. When $0 < d_{UR} < \theta$, EN_UGC is almost the truth, the firms can meet the challenges from EN_UGC effectively. Otherwise, the negative UGC is a rumour. According to Barone [2009], when firms receive rumour UGC, the best strategy is to release MGC promptly and courteously to change the direction of online opinion. As long as firms come up with convincing evidences, the rumour will lose its vitality and die out pretty soon. In this paper, we only take the case $0 < d_{UR} < \theta$ into consideration.

4. Modeling

4.1. Related communication principles

To build the model, we observe the following opinion propagation principles in social media:

First, fraction of selection or probability optimal principle. According to the fraction of selection principle, when Internet users facing the opinion from UGC or MGC, their probability to choose which kind of opinion is probably depends on the ratio of expected return and its vigorous magnitude. They are more likely to choose the opinion with optimal ratio of fraction of selection.

Second, homogeneity credibility principle. Internet users are more likely to trust the information from the same user groups. This greatly reduces the cost of interaction among Internet users. Compared to firms, each consumer can deem the other consumers belonging to the same group and firms as other group. According to homogeneity credibility principle, the online users will be more prone to accept UGC and reject the MGC.

Third, negativity effect principle. This refers to the tendency that people are more likely to pay high attention to negative evaluation than positive evaluation [Skowronski 1989]. Research indicates that negative information can attract more attention and more careful examination than positive one [Homer & Yoon 1992]. It is difficult for the consumers to determine the quality for experience products such as movies, caterings and games, negativity effect becomes more prominent [Hoch & Ha 1986]. Based on negativity effect principle, negative UGC will attract more attention from online users than positive UGC.

4.2. The lifecycle of EN_UGC propagation under interaction between EN_UGC and MGC

According to the three principles of opinion propagation, the mechanisms of EN_UGC propagation can be divided into the following four stages.

Stage I: EN_UGC active stage. EN_UGC is always unpredicted. When it occurs, the firm always needs time to investigate the incidents such as checking evidences, tracing the sources of the incidents, developing strategies to counteract the incidents. Simultaneously, according to the negativity effect principle, the public will be highly sensitive to the incidents. If they could not receive a response from the firm, they will speculatively decode and interpret the incidents. According to the fraction of selection or probability optimal principle, online users are more likely to accept the opinion that is easier to acquire, and then spread it. This leads UGC volume to increase exponentially. During this stage, the speculations of online users are always harmful to the firm. The firm is under great public opinion pressure.

Stage II: MGC release stage. With the acquisition of the truths of the event and timely announcements of MGC to the public, online users begin to read the content published by the firm. However, due to homogeneity credibility principle and negativity effect principle, the MGC can seldom take effect immediately. On the contrary, it might spur another tide of UGC propagation.

Stage III: MGC and UGC interaction stage. After the firm fully finds out the truths of the event and come up with strategies to tackle negative UGC, the firm will deploy various tactics in its media tool box to clarify the incidents hoping to minimize the negative effect from UGC as quickly as possible. If effective, the firm media strategy can change the direction of public opinion. The online users may then have a tendency to brows MGC. After a period of time, MGC will surge and compete head-to-head with UGC.

Stage IV: EN_UGC dying down stage. Though UGC are generated spontaneously and can be increased exponentially, its consistency and persistence are usually poor. MGC will be carefully crafted with the goal to eliminate the negative impact of EN_UGC at the largest possible extent. With the distribution of a firm's MGC, more and more online users begin to accept MGC. As a result, MGC becomes dominant and EN_UGC dies down.

4.3. Model of EN_UGC propagation considering the effect of MGC

In order to simplify our model, we make the following assumptions:

First, the main source of EN_UGC is microblog (such as Twitter, SinaWeibo etc.) where some online users post EN_UGC related with the firms while other online users read and follow the posted EN_UGC, and repost the EN_UGC. As a response, firms can try to affect users' perceptions by posting MGC on the same platform.

Second, the total number of users is time-variant. This means that the total number of users changes as time goes by. At time t, some users join the social media outlets while some users leave the social media outlets.

Third, only one firm creates MGC and online users will discuss and response to MGC. Simultaneously, we assume that the cost for both MGC and online users to search and forward UGC or MGC is small.

Fourth, the firm releases MGC toward truth in order to maintain its brand value. Thus, once users forward MGC, they can no longer be influenced by UGC.

Fifth, we divide the online users in microblog into two categories. The first is the ones who have not involved with the relative topics, assigned with identifier A; the second is the ones who have engaged with relative topics, assigned with identifier B. We further divide the second category based on whether they accept and then transmit the information. 1) Identify the users who accept EN_UGC as B1, users who accept MGC topic as B2, and users who hold neutral attitude as B3. 2) Identify users who both accept and transmit EN_UGC as U11, users who accept but not transmit EN_UGC as U12, users who both accept and transmit MGC as M11, and users who do not transmit MGC as M12. As the users of identifier A, B3, U12, M12 do not have much influence on the opinion transmission, in order to avoid complexity to establish the model, we unify these users as one category, which is labelled as N0. Our classification of users in EN_UGC propagation process is shown by Figure 1.

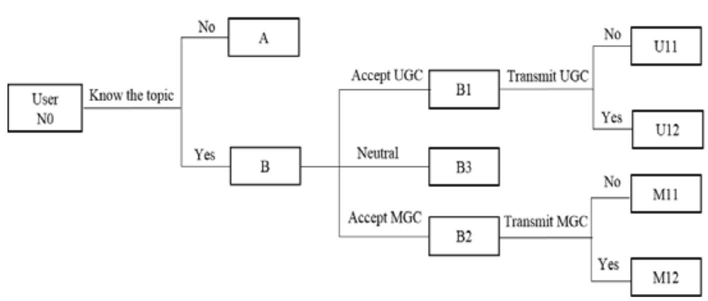

Figure 1: The users' categories of EN_UGC propagation model

Finally, we take the users of these identities into four groups: User subgroup $\mathrm{G_0} = \{\mathrm{N0}_i(t)\}$, where $\mathrm{N0}_i(t)$ represents the user i as N0 at time t, user subgroup $\mathrm{G_U} = \{\mathrm{U11}_i(t)\}$,where $\mathrm{U11}_i(t)$ represents the user i as U11 at time t, user subgroup $\mathrm{G_M} = \{\mathrm{M11}_i(t)\}$, where $\mathrm{M11}_i(t)$ denotes user i as M11 at time t, and user subgroup $\mathrm{Q} = \{q(t)|q(t-1) \in \mathrm{G_U}$ or $\mathrm{G_M}, q(t) \in \mathrm{G_0}\}$ denotes the quiet group, where q(t) represents the user who accepts one opinion (UGC or MGC) at time t-1, but quiet from the group $\mathrm{G_U}$ or $\mathrm{G_M}$ at time t. Therefore, the interplay process between UGC and MGC can be reflected by UGC dissemination, MGC influence and interest loss state. UGC dissemination and MGC influence are measured by the forwarding quantity of UGC and MGC respectively. The interest loss state is measured by migration quantity from the two groups of forwarding information. The variables U(t), M(t), and Q(t) respectively denote UGC dissemination, MGC influence and interest loss state. Moreover, we regard U(t), M(t) and Q(t) as the state variables of three user groups G_U, G_M and Q respectively, and the interaction between EN_UGC and MGC can be assumed as a continuous process.

Figure 2 shows a concise block diagram that illustrates the dynamical transmission of two pieces of competitive information among users. In the figure, each rectangle represents a subgroup which the social media users belong to. The directed lines denote the potential transition paths from one subgroup to another one. Table 2 explains the notations used in this study.

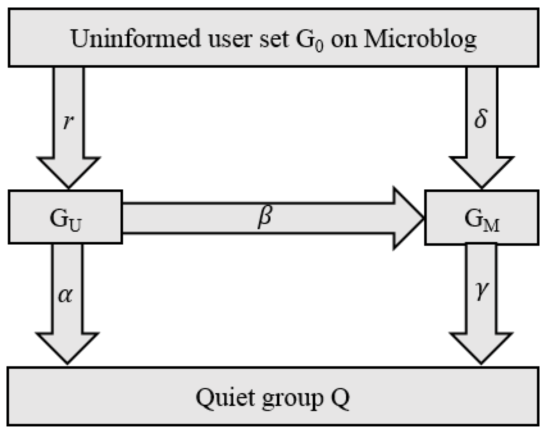

Figure 2: The subgroups and subgroup transitions in propagation of EN_UGC

Table 2: Notations and variable descriptions

Variable type	Notation	Definition
State variable	$U(t)$	Proportion of users forwarding UGC at time t
	$M(t)$	Proportion of users forwarding MGC at time t
	$Q(t)$	Proportion of users not forwarding any information at time t
Probability variable	r	Input rate of subgroup G_U
	α	Output probability of subgroup G_U
	β	the effectiveness of MGC on EN_UGC
	δ	Input probability of subgroup G_M
	γ	Output probability of subgroup G_M
UGC factor	d_{UR}	Deviation distance
MGC factor	ΔT	The interval between the first MGC releasing time and UGC publishing time
	ID	Average interval duration between the last MGC releasing and subsequent MGC releasing
	Fr	Average interaction frequency during the lifecycle of UGC propagation
	Q_M	Average information quantity of all MGC

In order to understand the correlation among the three subgroups G_U, G_M and Q, we analogize the effect of MGC to the epidemics. First, the effect of MGC can be described by the number of users who forward the MGC over time on social media, which is similar to the immunity mechanism of the epidemics [Zhao et al. 2009]. Second, to keep a higher total volume of unbiased word of mouth, the firm should motivate online users to retransmit MGC, which is similar to taking measures to increase the immunity probability of epidemics. Third, the effect of MGC on EN_UGC is not determined by one user or several users but by the collective behavior of many users. Thus, it is plausible for us to construct the dynamical model to investigate the interaction between MGC on EN_UGC based on prior studies [Zhang et al. 2012].

The interpretation for the change over time in the size of the group G_U is as follows. Due to uninformed users are connected to the social media, the concentration of G_U increase by parameter r at any time. However, the output depends on two factors. For the direct decreasing rate, once the message spreaders of UGC becomes bored and loses their interests in the topic, they will become into the quiet group. In this case, we adopt the standard incidence rate, i.e., $\alpha U(t)$. For indirect decreasing rate, when a spreader of UGC contacts another spreader of MGC, the MGC infects the spreader of EN_UGC at the probability β, and then the spreader becomes a member of G_M at a rate of $\beta U(t)M(t)$. Consequently, the change over time in the size of the group G_U is:

$$\frac{dU}{dt} = r - \alpha U - \beta UM \tag{1}$$

For the MGC to take effect in social media, on the one hand, there are $\beta U(t)M(t)$ from the subgroup G_U to the subgroup G_M. On the other hand, the MGC is discharged by the spreader of MGC, and the quantity discharged per unit time is $\delta M(t)$. However, for the spreader of MGC, after forwarding the MGC, (s)he will lose interest in the topic, and subsequently becomes the quiet group at a output rate from G_M $\gamma M(t)$. Thus, the change over time in the size of the subgroup G_U is

$$\frac{dM}{dt} = \beta UM + \delta M - \gamma M \tag{2}$$

When informed users forward MGC or EN_UGC in social media, they can lose interests in the topic discussion. Thus, the change over time in the size of the quiet group only consists of the input, and the input rate is $\alpha U(t) + \gamma M(t)$.

Integrating the equations (1) and (2), we build the dynamic behavioral model (3) to investigate the interaction between EN_UGC and MGC. Table 2 provides the parameter descriptions for model (3).

$$\begin{cases} \dfrac{dU}{dt} = r - \alpha U - \beta UM \\ \dfrac{dM}{dt} = \beta UM + \delta M - \gamma M \\ \dfrac{dQ}{dt} = \alpha U + \gamma M \end{cases} \tag{3}$$

Where

$r(t)$ indicates the input rate of subgroup G_U. It represents the volume of those who are active in social media at time t-1 and retransmit EN_UGC at time t;

$\alpha(t) = \frac{a_1}{a_2}$ denotes the output probability of the subgroup G_U, where a_1 is the number of those who retransmit EN_UGC at time $t-1$ but quit at time t, and a_2 is the number of those who retransmit EN_UGC at time $t-1$;

$\beta(t)$ represents the coefficient of the effect of MGC on EN_UGC. It is the ratio of users who retransmit EN_UGC at time $t-1$ but change the prior opinion to retransmit MGC at time t;

$\delta(t) = \frac{b_1}{b_2}$ denotes the input probability of the subgroup G_M, where b_1 is the number of those who do not retransmit MGC at time $t-1$ but repost it at time t, and b_2 is the number of those who do not retransmit MGC at time $t-1$;

$\gamma(t) = \frac{c_1}{c_2}$ denotes the output probability of the subgroup G_M, where c_1 is the number of those who retransmitMGC at time $t-1$ but change to quiet group Q at time t, and c_2 is the number of those who retransmit MGC at time $t-1$.

4.4. Analysis of EN_UGC propagation model

To investigate the effect of MGC on EN_UGC by our dynamical model effectively, we should understand the stability of the equilibrium of the model. Considering the specific feature of the third equation in Model (3), the state equations in Model (3) can be rewritten as:

$$\begin{cases} \dfrac{dU}{dt} = r - \alpha U - \beta UM \\ \dfrac{dM}{dt} = \beta UM + \delta M - \gamma M \end{cases}$$

(4)

To determine the equilibrium of equations (4), let

$$\begin{cases} \dfrac{dU}{dt} = r - \alpha U - \beta UM = 0 \\ \dfrac{dM}{dt} = \beta UM + \delta M - \gamma M = 0 \end{cases} \tag{5}$$

Solving (5), we can obtain
$M = 0$ or $\delta + \beta U - \gamma = 0$
(i) When $M = 0$, solving $r - \alpha U - \beta UM = 0$, we can get $U_0 = \frac{r}{\alpha}$. Therefore, we capture the MGC-free equilibrium $I_0 = (\frac{r}{\alpha}, 0)$. (ii) When $\delta + \beta U - \gamma = 0$, solving $r - \alpha U - \beta UM = 0$, we can obtain $U^+ = \frac{\gamma-\delta}{\beta}, M^+ = \frac{r}{\gamma-\delta} - \frac{\alpha}{\beta}$. Since we consider the case at $U > 0$, we assume that $\gamma > \delta$. Hence, MGC-UGC equilibrium will be:

$$I^+ = (U^+, M^+) = (\frac{\gamma-\delta}{\beta}, \frac{r}{\gamma-\delta} - \frac{\alpha}{\beta}) \tag{6}$$

We have solved the two equilibriums for equations (4). Now, let us turn to the stability of the equilibrium of equations (4).

To achieve the stability of the equilibrium for equations (4), we suppose the threshold $T_0 = \frac{\beta r}{\alpha(\gamma-\delta)}$, which is regarded as reproductive number of MGC in order to affect EN_UGC. T_0 is a reference point to predict whether the influence of MGC on UGC will increase or decrease. Meanwhile, we build the feasible region $\Omega = \{(U, M) | U, M > 0, U + M \leq \frac{r}{\alpha}\}$. From the expression of T_0, we can infer that $T_0 \leq 1$ or $T_0 > 1$.

Theorem 1. The MGC-free equilibrium I_0 is globally asymptotically stable if $T_0 \leq 1$.

Proof. Taking the equilibrium $(U_0, 0)$ to the origin by virtue of a coordinate transformation $u = U - U_0$, equations (4) can be rewritten as

$$\begin{cases} \dfrac{du}{dt} = -\alpha u - \beta(u + \frac{r}{\alpha})M \\ \dfrac{dM}{dt} = \beta\left(u + \frac{r}{\alpha}\right)M + \delta M - \gamma M \end{cases} \tag{7}$$

Where $(u, M) \in \Omega^{'} = \{(u, M) | u + U_0 > 0, M > 0, u + M \leq 0\}$.

Applying Lyapunov Direct method, we consider the following candidate function

$$L_1 = \frac{u^2}{2} + U_0 M$$

Clearly, L_1 is positive. The time derivative of L_1 along an orbit of equations (7) is

$$\begin{aligned} \frac{dL_1}{dt} &= -\alpha u^2 - \beta\left(u + \frac{r}{\alpha}\right)uM + \frac{r}{\alpha}\left[\beta M\left(u + \frac{r}{\alpha}\right) + (\delta - \gamma)M\right] \\ &= -\alpha u^2 - \beta u^2 M + \frac{r}{\alpha}M[\frac{\beta r - (\gamma - \delta)}{\alpha}] \end{aligned}$$

If $T_0 \leq 1$, and $\beta r - (\gamma - \delta) \leq 0$, the derived function of L_1 is not positive in $\Omega^{'}$. It can be verified that $\frac{dL_1}{dt} = 0$ if and only if $(u, M) = (0,0)$. Besides, $L_1 \to \infty$ as $u \to \infty$ or $M \to \infty$. It follows from the LaSalle Invariance Principle that I_0 is globally asymptotically stable with respect to Ω if $T_0 \leq 1$. This suggests that the firms do not release any effective MGC to respond to EN_UGC.

Proposition 1. (**Runaway mode**) The effectiveness of the firm's MGC strategy on EN_UGC will eventually die out if and only if $\beta r / (\alpha(\gamma - \delta)) \leq 1$. We call this case as runaway model.

Proposition 1 identifies the condition where the firm's MGC strategy fails to work. Let us use DELL example [Brian 2012] to demonstrate proposition 1. Online computer retailer Dell Inc. reacted to popular blog from consumerist.com article "22 confessions of a former Dell sales manager" with a cease and desist letter in June 2007. But the heavy-handed response to the negative blog post did not have the intended effect. Instead, it garnered more negative publicity than the original post [Jackson 2008]. Such a grim situation can be illustrated by our model. Because of the strict and harsh response from Dell, users are provoked, which increases the input rate r of subgroup G_U. Those users who should have quitted from the subgroup G_U did not quit. Although Dell posted a blog of their own on their Direct2Dell blogging site admitting they were wrong and dropped the case, they were just getting slammed in social media. In other words, in this case, it is more difficult to control the spreading of EN_UGC. The main reason is that DELL's action makes the input rate δ of subgroup G_M becomes much lower, and the thus response is in effective in increasing input rate r for subgroup G_U and decreasing output rate α for subgroup G_U.

Proposition 1 also shows that the EN_UGC will slow down on its own, allowing the firm not to respond, otherwise the situation will become much worse than it should be. Due to the information update in social media, EN_UGC will be getting less and less attention as time goes. Moreover, online users generally have short attention spans, and users are information overloaded in the digital world [Vogt 2009]. Therefore, it is possible that emerging hot topics would divert users' attention away from the current EN_UGC. The result is that input rate r of the subgroup G_U is quite small while the output rate α of the subgroup G_U is much big. That is to say, what outrages the public tends to rise and fall quickly as the next new UGC emerges in social media. Thus, the life cycle of EN_UGC depends on forget-remember mechanism of users. The runaway model thus suggests that the firm does not need to release MGC to respond to the EN_UGC because MGC will not change the dynamics of EN_UGC's propagation, and the action may make the situation worse.

Theorem 2. The MGC-UGC equilibrium I^+ is globally asymptotically stable with respect to Ω' if $T_0 > 1$.

Proof. For stability of I^+ in equations (4), we transform the equilibrium to the origin using the coordinate transformation for equations (4):

$$\begin{cases} u = U - U^+ \\ m = M - M^+ \end{cases},$$

therefore equations (4) can be rewritten as

$$\begin{cases} \dfrac{du}{dt} = -\alpha u - \beta u\left(\dfrac{r}{\gamma-\delta} - \dfrac{\alpha}{\beta}\right) - (\gamma-\delta)m \\ \dfrac{dm}{dt} = \beta u\left(m + \dfrac{r}{\gamma-\delta} - \dfrac{\alpha}{\beta}\right) \end{cases} \tag{8}$$

Applying the Lyapunov function, we have

$$L_2 = \frac{u^2}{2} + \frac{(\gamma-\delta)(m - lnM/M^+)}{\beta},$$

We can see that L_2 is the positive with respect to (U^+, M^+). The time derivative of L_2 along an orbit of equations (8) is

$$\frac{dL_2}{dt} = -\alpha u^2 - \beta u^2 M^+.$$

It suggests that $u = 0$ be necessary and sufficient for $\frac{dL_2}{dt} = 0$; Additionally, if $u = 0$ is the solution for equation (8), then $e = 0$ (i.e., $M = M^+$). Therefore, the set of solutions for equation (8) meeting $\frac{dL_2}{dt} = 0$does not include the non-trivial solution. The equilibrium I^+ keeps global asymptotic stability in feasible region Ω, while I_0 is unstable.

Proposition 2. (**Effective mode**) The effectiveness of firms' MGC strategy on UGC can go on for a long time if and only if $\beta r/(\alpha(\gamma-\delta)) > 1$. This case is called effective mode.

Proposition 2 tells us, the relationship between the two kinds of information is competing where one type of information suppresses the other type of information in effective mode. Therefore, in order to decrease the negative effect of EN_UGC and increase the maximum coverage of MGC, firms should take actions to control the system parameters so that T_0 is remarkably above one. Clearly, firms can control the parameters β and δ by virtue of the expression of T_0, which represents the effect strength of MGC on EN_UGC and the input rate of the subgroup G_M respectively. However, it is difficult to control the remaining parameters in social media simultaneously. To find key factors to affect the effectiveness threshold T_0, it is necessary to examine the sensitivities of T_0 to parameters β and δ respectively.

Following Arriola and Hyman [2005], the normalized forward sensitivity indices with respect to β and δ are calculated respectively as:

$$\frac{\partial T_0/T_0}{\partial\beta/\beta} = \frac{\beta}{T_0}\frac{\partial T_0}{\partial\beta} = 1 > 0$$
$$\frac{\partial T_0/T_0}{\partial\delta/\delta} = \frac{\delta}{T_0}\frac{\partial T_0}{\partial\delta} = \frac{\delta}{\gamma-\delta} > 0 \tag{9}$$

Sensitivity analysis (9) suggests that for the two parameters β and δ, T_0 is more sensitive to the change of β. Indeed, an increase in β will yield an increase of the same proportion in T_0 (equivalently, a decrease in β will lead to an equal decrease in T_0; they are directly proportional). This shows that the effectiveness threshold presents fast growth when the effect strength of MGC on EN_UGC (β) increases, while the effectiveness threshold keeps growing slowly as the input rate δ of the subgroup G_M increases. To illustrate the above results better, we present the tendency of effectiveness threshold in Figure 3.

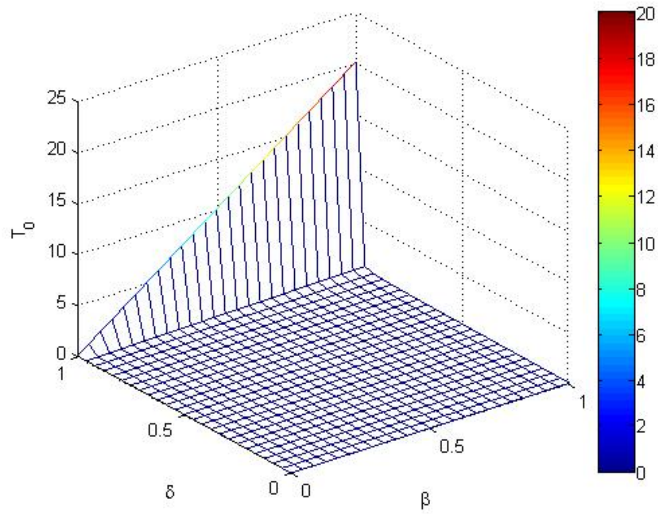

Figure 3: Effectiveness threshold depicted against β and δ

Our results and Figure 3 suggest that extreme strategies (i.e., deleting post and employing paid posters) deployed to deal with EN_UGC are not effective (The purpose of these two strategies are to reduce the possibility of users reading the EN_UGC, i.e., decrease the input rate r of the subgroup G_U in our model). However, in effective mode, we can see that decreasing the input rate r not only cannot increase the number of users in subgroup $G_{U,}$ but also decrease the number of users in subgroup G_M. The results can also be reflected by the MGC-UGC equilibrium, in which the number of forwarding EN_UGC is not related with parameter r (See MGC-UGC equilibrium I^+). In effective mode, our model and Figure 3 suggest that a firm should adopt the following strategies to mitigate the influence of EN_UGC:

First, increasing parameter β. The firm should increase its interaction frequency Fr with users in the subgroup G_U to influence the users' early perception and turn them into MGC sponsors and advocates. This strategy is consistent with prior studies suggesting that online management responses increase future satisfaction of the complaining customers who receive the responses [Gu & Ye 2013, Homer & Yoon 1992].

Second, increasing parameter δ**.** The firm should reduce the response time for EN_UGC (ΔT) and the average interval duration ID, release the sufficient information to consumers (Q_M), such that it can switch more users from subgroup G_0 to subgroup G_M, which can maximize the influence of MGC.

In addition, attention should be paid to parameter r**.** Firms should not try to delete postings and employ paid posters. On the contrary, firms should try to increase parameter $r$change as it should be because this can accelerate spread of MGC (See MGC-UGC equilibrium I^+).

Third, our results and Figure 3 also have implications for lifecycle management of EN_UGC propagation. In EN_UGC active stage, Internet users should be urged to acquire the truth of the negative postings. Simultaneously, we urge firms to increase Fr with potential users, identify key nodes, and gather user information demand. The nature of these strategies during this stage is to decrease input rate r of the subgroup G_U and increase the output rate α of the subgroup G_U. These strategies aim to reduce the coverage of EN_UGC before releasing MGC.

Fourth, in MGC release and MGC-UGC competition stages, on the one hand, firms should release proper amount of MGC (Q_M) and employ public figures with social influence or opinion leaders to post MGC to increase the input rate δ of the subgroup G_M. On the other hand, firms should interact with users in the subgroup G_U to increase the effect strength of MGC on EN_UGC (β). Such strategies at this stages can effectively dilute the influence of EN_UGC and magnify the influence of MGC.

Fifth, in EN_UGC dying-down stage, firms should try their best to reduce the quantity of MGC and prolong the average interval duration ID between the last MGC releasing and subsequent MGC releasing. In this stage, EN_UGC and MGC are both controlled to steady states and transition probability of users will not change again. Releasing more information can inversely lead users to lose interest in MGC to increase the output rate γ of the subgroup G_M while decrease the input rate δ of the subgroup G_M because excessive information can cause online users to generate negative mentality and negative behaviour responses [Vasterman 2005].

5. Conclusion and future research

Recent advances in information technologies have made it easier for individuals to post their opinions and experiences about firms' products/services in social media. Such behaviours can be both blessings and curses as indicated by prior studies. The purpose of this study is to offer optimal MGC strategies for firms to deal with EN_UGC. We built a dynamical model of EN_UGC propagation considering the performance of MGC in defending against EN_UGC propagation by taking MGC adopters as a subgroup. We analysed the stability of the equilibrium of the model and proposed Theorem 1 and 2, and Propositions 1 and 2.

Although this research shows some important results, other problems still remain unresolved. First, for model parsimony, we were unable to integrate the microfoundation of MGC and EN_UGC into our model. Also, formulating effective MGC to respond to EN_UGC can be costly. Including cost into our current model would make it too complex for us to mathematically handle the modeling process. Thus, future research can build on our research to explore the microfoundation of EN_UGC and MGC interaction and take other factors such as MGC strategy formulating cost into the model. Second, we built a mathematical model and explored the conditions under which MGC can have impacts on EN_UGC. However, due to data availability, we were not able to empirically test our model. Future research can collect data to empirically test the proposed model. For example, future research can survey a large sample of firms to see which strategies firms have deployed to combat such UGC and why they selected those strategies would be a useful extension of this study. It would also be interesting to see which variables might moderate the effectiveness of a particular strategy, such as firm size (i.e., small versus large), the particular industry (i.e., services versus manufacturing), or the corporate culture (i.e., open versus closed). Clearly, firms need to know more about how to deal with EN_UGC and much work is needed to continue to shed light on this complicated issue. Hopefully our exploratory work can inspire interesting future research.

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