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To Share or Not to Share? Branded Content Sharing in Twitter

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Abstract – Marketers have long recognized the power of word-of-mouth communication to influence consumer brand perceptions. Social media channels such as Facebook and Twitter make possible an efficient spread of communication to potentially large audiences with the added value of the credibility afforded to earned media. Consequently, marketers seek to encourage social media users to share brand-related messages. But how? To answer this question, we must first understand the decision to share or not to share in a social media context. This paper reports on an investigation as to the source and content of a brand's tweets as antecedents of an individual's decision to share that tweet among his/her followers. Our data show that both source and content interact to influence the share decision. Implications and future research are discussed.

Keywords – social media, message amplification, content marketing, social sharing, diffusion of information

Relevance – This article reports the results of two studies which investigated the effect of branded content type and type of brand on message sharing in social media. The results provide guidance on the development of branded content for social media managers.

Introduction

Social media messages that "go viral," spread by and to the masses influence our collective consciousness and provide for a shared cultural experience. Such messages are not necessarily branded or brand-related. Many are user-generated entertainment (e.g. Charlie Charlie), public interest stories (e.g., the spread of the story of the moviegoer who reprimanded a teen's behavior (http://www.popsugar.com/ moms/Mom-Praised-Reprimanding-Misbehaving-Daughters-37180109), and even societal calls to action (e.g., #YesAllWomen). Messages spread as people share others' content with their own social graphs, and recipients share, and so on, creating a cascade of information (Tuten and Solomon, 2015). Overall, reach is maximized when those who share content have credibility and a large network size. But what are the content factors that inspire sharing among social media users? To answer this question, we must first understand the decision to share or not to share in a social media context. By understanding the sharing decision, we may then systematically design messages to enhance the extent to which these messages are shared, known as message amplification.

In this paper, we describe the results of a study designed to examine the determinants of share behaviors, and specifically the resharing of content. Share behaviors are necessary to accomplish message amplification and reach objectives in social media marketing campaigns. In addition, reshared content may be perceived as higher value content given the referral value of the referrer. From a practitioner standpoint, message amplification and reach has thus far been accomplished primarily through the use of "seeding." Seeding refers to the tactic of identifying opinion leaders and incentivizing them to share the target content with their social graphs (Yeo, 2012). New research identifies social media influencers, who have considerable network power, but who may or may not meet the definition of opinion leader (Kay, Mulcahy, and Parkinson, 2020, Kumar and Mirchandani, 2012).

Researchers have investigated a variety of variables to explain message amplification including tie strength of network members, user personalities, individual motivation and strategies for identifying influentials (Dodds and Watts, 2007). More recently, other explanations for understanding the diffusion or sharing of social media content have been offered including the role of emotions in inspiring viral spread of messages (Fractl, 2016), user motivations (Apuke and Omar, 2021), the message characteristics specifically the use of alliteration and repetition in message rhetoric (Ordenes, et al., 2019), and user mobility (Wang, et al., 2021). That said, research on the content characteristics of branded messages associated with the likelihood of message amplification is extant. This research addresses that gap by examining the effect of type of brand content on individuals' decision to share in social media by type of brand (personal versus consumer product). From a marketing management perspective, the results offer social media managers guidance on the development of content with a high probability of reach and earned media impressions.

Literature Review

Social media have become a standard component of brand marketing communications efforts. According to SproutSocial, 89% of marketers use Facebook to spread brand messages and reach target audiences (Zote, 2020). On Facebook, brands post a median of .97 posts per day and earn a median engagement rate of .09% across all industries (Zote, 2020). Ninety percent of Instagram users report following a brand on the platform and brands on Instagram earn a median engagement rate of 1.60% across all industries (Zote, 2020). On Twitter, brands post a median of 0.86 tweets per day, for which they see a median engagement of 0.048% (Zote, 2020). These brand messages have increased reach and exposure when they are shared by the audience resulting in diffusion of the information and message amplification. These influence impressions are influential in part because of the credibility inferred by the source of the shared content. Just as word-of-mouth communication offline is more influential when the source is perceived as credible, communication shared in social media channels also benefits from the source (Duan, Gu and Whinston, 2008; Jansen, Zhang, Sobel, and Chowdury, 2009).

Companies seek ways to leverage social media and drive engagement to in turn drive purchase intention and loyalty. Studies have investigated how social media can influence purchase decision and opinion formation across different cultural dimensions (Goodrich and de Mooij, 2014). Research has shown that eWOM, product category, number of postings and their interaction with the product can explain changes in sales (Davis and Khazanchi, 2008), thereby making a company's content strategy on social media relevant to more than just brand awareness, image or familiarity. It can also affect purchase intention.

Empirical research on diffusion and social word-of-mouth communication has largely focused on seeding content with influentials (Bakshy, Hofman, Mason and Watts, 2011) or studying diffusion patterns (Godes and Mayzlin, 2004; Watts and Dodds, 2007). Other efforts have looked at user emotions (Berger and Milkman, 2012, Fractl, 2016) and user motivations and channel of communication (Berger and Iyengar, 2013) as factors. Berger and Milkman (2012) found that positive content valence and content that evokes arousal is more viral. Fractl (2016) found that the emotions inspired by content contributed to the viral spread of messages. Specifically, positive emotions including amusement, interest, surprise, and happiness were associated with the spread of messages. For example, the spread of the viral video called "Chewbacca Mom," the most shared Facebook Live video, promoted the emotions of amusement, interest, and happiness. Audiences could share these positive emotions by sharing the video (Fractl, 2016). Another example is the "America's Favorite Dog" infographic which promoted joy, happiness, and delight. It earned thousands of social shares and generated publicity on sites like Mashable (Fractl, 2016).

Those who share may also have different motivations. For instance, narrowcasting consumers (focused on others) share more useful/utilitarian content with their smaller audience (i.e., don't worry as much about how the content makes them look) while broadcasting consumers (focused on self) share more self-presentation content with their larger audience (i.e., content that makes them look good) (Barasch and Berger, 2014).

In a study on the spread of health-related social content, researchers found that whether a social media user has the willingness to share is mainly related to source credibility (institution-based trust). Content credibility was also related to sharing willingness although not as strongly as source credibility (Jin, Yin, Zhou, and Yu, 2021). Moreover, content credibility has a stronger relationship with adoption willingness than with sharing willingness, while institution-based trust shows a stronger relationship with sharing willingness than with adoption willingness. Similarly, Liu, Chen, and Fan (2021) explored the diffusion of crowdfunding campaigns and found that the digital reputation of the founder was the most influential variable in explaining the spread of the fundraising initiative. Wang, et al., (2021) reported that users' mobility increases the connections among users and expands the diffusion of information.

Little research exists that explores the effects of content type on message sharing. Wu, Hofman, Mason, and Watts (2011) found that the content with the longest lifespan were videos and music while media originated URLs had the shortest. This implies that content type may covary with sharing. Ordenes et al. (2019) conducted an image-based study that demonstrated that the presence of visuals was related to message sharing. While brands are widely encouraged to utilize video posts and short-term content like Instagram Stories to enhance exposure, attention, and engagement, little is known about whether such forms of content influence sharing behaviors among social media users.

Branded Content and The Value of Message Amplification

Drawing from the diffusion and WOM literature, we take the research in a new direction by assessing the influence of content and brand type on the propensity for individuals to share branded content. We focus on the effect different types of content and brands have on achieving engagement through retweets.

As customers are more connected and engaged, content becomes key for marketers to influence and reach new and existing customers (Hanna, Rohm, and Crittenden, 2011). When customers share brand content, they engage in a form of eWOM as they essentially become marketers for the brand. First, the sharing of branded content enables brands to broaden their reach as information cascades through social networks. When brands broadcast social messages, they typically divide their content between other-focused content (useful/utilitarian content that is relevant to the audience) and content that is self-focused (content that directly promotes the brand). Branded content may include organic content developed and posted by a brand, as well as paid social content including social ads and promoted posts. (Lipsman, Mudd, Rich, and Bruich, 2012). The reach of branded content among *friends of fans* exceeded the reach among fans. Thereby, content marketing as a strategy is more successful if the content gets re-shared by the audience to their social graphs.

Second, shared brand content may be imbued with more credibility. Since customers still put more trust in messages from peers than from companies, by sharing brand content, customers are telling their peers that the information is to be trusted and adding trust equity to the message. In short, they are making their peers more receptive to the brand's message than if they were exposed to the original message by the brand. This provides customers "tremendous clout" on influencing brand image and perceptions (Jansen, Zhang, Sobel, and Chowdury, 2009; Reynolds, 2006; Urban, 2005)

Twitter is particularly popular among those under 50 and the college-educated, making the microblogging platform an attractive medium for brands to engage with customers and promote their brand (Duggan, Ellison, Lampe, Lenhart and Madden, 2015). As Twitter more closely resembles an information network rather than a social network, it provided the perfect context to evaluate how the interaction of content type and brand focus drives the sharing of branded content through retweets. Therefore, evaluating whether different types of content are shared is relevant.

To date, most information on content strategies have been prescriptive rather than empirically based guidance. Industry experts and institutes including the Content Marketing Institute compel marketers to develop content for social media channels that includes varying levels of content originality and quality, graphics and video, links, and text infused with so-called linkbait (the industry term for writing in a way that encourages the audience to view and/or share the post). Linkbait includes several executional appeals including lists, resource hooks, humor, giveaways, research results, and how-to hooks (Tuten and Solomon, 2015). Depending upon the industry and target audience interests, posts may provide pictures, video links, infographics, links to case studies and white papers, links to presentations, news, announcements, quotes, and conversation. Despite the plethora of practitioner advice, little is known about the relative effectiveness of these forms of content in generating sharing behavior. To that end, we conducted two exploratory studies to answer the research question, "To what extend does content type and brand type explain whether content is reshared?"

While the research in this area has tended to utilize news articles as the content object, we sought to increase the relevance of the research for marketing managers by utilizing many content types. We compiled a list of different content strategies recommended for brands (Tuten and Solomon, 2015). The categories of content included in the studies were conversation, list, resource, humor, giveaway, counter-belief, how to, curated content, video link, picture, infographic, news, research/stats, case study, slide share presentation, quote and announcement. In addition, we studied two types of content source: 1) consumer-packaged (CPG) goods brands and 2) personal brands (people). Thus the two studies provided insight into what types of content had the highest probability of message amplification and which source is most advantageous for message amplification.

Methods

We designed two exploratory studies to answer the research questions, "What types of content published in a social media channel have higher rates of resharing (message amplification)?" and "Does content shared by brand profiles differ in the rate of resharing compared to content shared by influential people?"

Study 1

We selected a set of four user profiles to serve as content sources. The selection criteria included matching for recent activity, follower size as well as the type of profile two CPG brands and two personal brands (individuals). For each profile type (CPG vs individual), we selected one well known profile and one average profile. To generate our sample we used the Twitter Application Programming Interface (API) with the twitteR package for R. We extracted the tweets generated by these four profiles for a limited period of time. Through the Twitter API site, we accessed 2,000 tweets total (500 most recent tweets for each brand). There were no promotions or any major events during the data collection period that could influence our data. Tweets originating with other Twitter users than the user account being examined chose to share were eliminated from the data set to focus specifically on the content generated by the brand accounts being investigated.

The content types identified in the literature were used as codes and the collected tweets were then content-analyzed. Tweets were coded by two analysts who had been trained in the identification of content types. When the analysts disagreed on categorization, the tweet was categorized by a principal investigator. The content codes included 17 content categories. Categorical variables were then converted to dummy variables using 1 for presence of the content type and 0 for absence of the content type. Retweets served as the dependent variable. Due to the small sample size, retweets were measured as a percentage of followers retweeting, to avoid confounds related to differences in number of followers across brands. Once data were coded, multiple regression analysis was used. Multiple regression was selected as it best suited the data with a single dependent variable (percent of follows retweeting) along with a set of independent variables corresponding to content and user factors.

We performed six regressions total: one for each brand (CB_A, CB_B, PB_A, PB_B,), one for the two consumer goods brands (CB_R) and one for the two personal brands (PB_R). CB_R (R^2 = .11) results showed giveaways and announcements having a positive effect and conversations a negative effect on retweets (p<.01).

Individual results showed that CB_A (R^2 = .20) with infographics (p<.05) and announcements (p<.01) positively affecting and conversations (p<.01) negatively affecting retweets. In contrast, CB_B (R^2 = .42) had conversations and announcements negatively affecting (p<.01) and pictures positively affecting (p<.01) retweets.

PB_R (R^2 = .35) results showed curated content, video links, news, and research/stats having a positive effect (p<.01) and pictures (p<.05) a negative effect on retweets.

Individual results showed that PB_A (R^2 = .35) with picture and case studies positively affecting (p<.01) and resources (p<.05) negatively affecting retweets. In contrast, PB_B (R^2 = .45) had resources and announcements negatively affecting (p<.01) and conversations positively affecting (p<.01) retweets.

Study 2

In study 2, much the same approach was used as in study 1 though a larger set of profiles was included. While study 1 included data originating from the tweets of four profiles, study 2 included tweets originating from 14 profiles. As in study 1, the selection criteria included matching for recent activity, follower size as well as the type of profile four CPG brands and ten personal brands (individuals). Data for the study was collected using the Twitter API using the twitteR package for the R programming language. The Twitter API delivers information on a best-effort basis, meaning that not all requested information will necessarily be returned. "Our search service is not meant to be an exhaustive archive of public tweets and not all tweets are indexed or returned." Thus, while a corpus of 500 tweets from 14 different user accounts were requested from the API, only 6946 raw tweets were delivered for study. This number included "retweets" meaning tweets originating with other Twitter users that the user account being examined chose to share. These retweets were eliminated to focus specifically on the content generated by the accounts being investigated. The final total for tweets was 5965 generated by 14 accounts, 10 personal brands and 4 consumer brands. Tweet count ranged from a minimum of 300 to a maximum of 496 per account.

As in Study I, each tweet was manually coded to identify the presence of the 17 content strategies. However, for Study II additional information obtained from Twitter was also used in the regression: whether the tweet was a reply to another tweet. In addition, since we had a bigger sample size and more variety of accounts, our dependent variable was the actual number of retweets. Two separate multiple regression analyses were used to determine the impact of content strategies for personal brands and consumer brands. The dependent variable in each case was the number of retweets for a particular message. For each analysis, regression through the origin (Eisenhauer 2003) was used to provide the best explanation of the different effects.

As seen in Table 1, the content factors (along with the information about whether the post was a reply) explained 13.8% of the variability in retweet count for consumer goods brands (CB_R) and 22.4% for personal brands (PB_R). One interpretation of this difference would be that for individuals the actual content of the messages plays a greater role in driving sharing than for consumer brands, where sharers may wish to demonstrate their affiliation with the brand itself.

Table 1. Regression results for consumer and personal brands.

	R	*R Squared*	*Adjusted R Squared*	*Std. Error of the Estimate*
Consumer brands	.372[a]	.138	.131	61.092
Personal brands	.473[c]	.224	.220	88.534

CB_R (R^2 = .138) results showed the following factors played a significant role in increasing retweets: humor ($p < .01$), giveaways (($p < .01$), how-to ($p < .01$), curated content ($p < .01$), video links ($p < .01$), and pictures ($p < .01$). Conversation proved to be a significant and negative factor for retweet count for consumer brands ($p < .05$). Whether or not the message was in reply to another message was not a significant factor.

PB_R (R^2 = .224) exhibited quite different results. Replies by personal brand accounts to other messages were significantly less likely to be retweeted ($p < .01$). Content factors conversation ($p < .01$), resource ($p < .01$), humor ($p < .01$), video link ($p < .01$), picture ($p < .01$), infographic ($p < .05$) and quote ($p < .01$) significantly increased the number of retweets for a particular message.

Discussion

Our results support that both type of source and type of content will impact whether an individual decides to share a brand's content. While there are general standards to create engagement with customers on social media, it is clear it is not a one-size-fits-all strategy. Certain types of content had higher message amplification whether the source was a brand or a person. These content categories included the use of humor in the message, inclusion of a video, and pictures. Thus, the prescriptive advice for brands to utilize video and images is supported. Giveaways and resource content like how-to articles also positively influenced the likelihood of sharing no matter which type of account was posting.

However, message amplification was higher for people tweeting conversational content but lower for brands tweeting conversational content. Prescriptive industry advice may encourage brands to behave as personas in social media channels, but that advice is not supported by our findings. Rather, conversational tweets by brands were less likely to be reshared. This result could indicate that most consumer brand conversations with a single user are specific to that user (e.g. "We are sorry that you had that experience.") and thus do not motivate resharing. Conversational dialog between individuals, on the other hand, may indicate a topic or debate that is worth spreading to one's own network. Overall, the results suggest that followers and fans may, whether consciously or unconsciously, perceive whether the source is human and expect certain types of content based on source categorization. These findings may suggest value in brands using spokespeople in social media channels to ensure message amplification of certain types of content.

Reply messages, where the message is directly responding to another profile, were also treated differently when posted by consumer goods or personal brands. For consumer goods, such message had no impact on amplification, but for individuals these messages had a lower rate of amplification. An inspection of reply messages from individual accounts suggest they contain little of benefit to others, instead including thanks or acknowledgements of the replied-to messages.

It is clear that consumer goods brands and personal brands need to follow different content marketing strategies if amplification through retweets is one of their goals. The followers of these type of brands value different types of content and clearly have different expectations. Brands would be wise to consistently look at their retweet data as a guide for content. Given the results above, social media brand managers (whether individual or consumer goods) might consider a portfolio of different message content with different expectations for the impact of message types. A consumer goods brand, for example, might do some conversational messaging to influence their perceived responsiveness, but should also do more brand building messaging with humor or media that will be more likely to be shared.

Our research goal was to test the success of common content marketing strategies in achieving amplification of the brand's message through retweets. As such it can serve as a guideline that different types of profiles – CPG brands versus individual – will need to follow different strategies within Twitter. The results of the studies inform content strategies for social media managers designing and publishing branded social content for marketing communications.

Future Research and Limitations

Our first study scratches the surface of a larger conceptual framework and only looks at two independent variables (source and content) as antecedents of the sharing effect. It is also limited to its Twitter context and the sample size (four brands total). In light of this for our second study we expanded our data set to 14 total brands (10 consumer brands and 4 personal brands) and five hundred tweets each. We only looked at the content through these 17 content codes and did not make any inferences or analysis in terms of other variables such as emotion elicited, time of day, demographics of user, etc. Those are certainly areas that are open to further research as is conducting similar research in other platforms such as Facebook, Pinterest, Instagram, etc.

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Appendix A - Regression Results

individual	Content Factor	Unstandardized Coefficients		t	Sig.
		B	Std. Error		
consumer brand	is reply	6.624	4.073	1.626	.104
	conversation	**-7.590**	**3.534**	**-2.147**	**.032**
	list	-5.892	35.407	-.166	.868
	resource	-4.427	10.360	-.427	.669
	humor	**63.461**	**6.048**	**10.493**	**.000**
	giveaway	**41.783**	**8.646**	**4.833**	**.000**
	how to	**33.155**	**7.575**	**4.377**	**.000**
	curated content	**19.114**	**6.513**	**2.935**	**.003**
	video link	**28.318**	**6.587**	**4.299**	**.000**
	picture	**10.860**	**3.075**	**3.532**	**.000**
	infographic	-8.576	64.476	-.133	.894
	news	-4.262	17.033	-.250	.802
	research/stat	-1.285	20.446	-.063	.950
	quote	-2.213	35.398	-.063	.950
	announcement	8.559	5.741	1.491	.136
personal brand	**is reply**	**-27.242**	**4.216**	**-6.462**	**.000**
	conversation	**26.333**	**3.580**	**7.356**	**.000**
	list	15.297	11.844	1.292	.197
	resource	**32.913**	**2.928**	**11.242**	**.000**
	humor	**90.295**	**4.172**	**21.642**	**.000**
	giveaway	59.781	44.817	1.334	.182
	how to	-8.148	15.178	-.537	.591

	curated content	-4.446	26.362	-.169	.866
	video link	**20.121**	**5.484**	**3.669**	**.000**
	picture	**15.773**	**3.560**	**4.431**	**.000**
	infographic	**26.818**	**12.376**	**2.167**	**.030**
	news	-5.079	5.079	-1.000	.317
	research/stat	2.116	9.844	.215	.830
	quote	**49.702**	**5.679**	**8.752**	**.000**
	announcement	8.582	6.371	1.347	.178
	case study	15.002	23.006	.652	.514
	counter-belief	131.000	88.534	1.480	.139
	slide share	70.140	39.689	1.767	.077