

REAL TIME IS REAL MONEY: THE EFFECTIVENESS OF RTM AS A STRATEGY TO INCREASE THE SHARING OF BRAND TWEETS

ABSTRACT

Twitter timelines are increasingly populated with brand tweets that are linked to public events, a practice that is also known as real-time marketing (RTM). In two studies, we examine whether RTM is an effective strategy to boost sharing behavior, and if so, what event- and content-related characteristics are likely to contribute to its effectiveness. A content analysis of brand tweets from Nielsen's top-100 advertisers (n=1500) shows that not all events are equally effective. RTM is only a more effective strategy (vs. no real-time marketing), when brand messages are linked with unpredictable events but not when brand messages are linked with predictable events. In a follow-up study, we examined what content characteristics improve the shareability of predictable RTM messages. A content analysis of RTM messages (n=143) from the Forbes top-100 brands showed that predictable events yield more retweets when the event is visually integrated in the brand tweet (vs. not visually integrated). The presence of event-driven hashtags did not lead to more retweets. Implications for theory and practice are discussed.

INTRODUCTION

Social media were heralded for their potential to reach a public at large. Consumers organized themselves as networks of fans, followers and friends around branded social media profiles. Without allocating enormous advertising budgets, messages from brands could be easily pushed through these communities and beyond, due to the networked nature of social media, and the ability to pass along messages in real time (Fournier & Avery, 2016).

Ten years later, we've learned that organic reach on social media is not a known fact. As brand activities migrated to social media, the timelines of Facebook and Twitter became cluttered. In response to this development, social media such as Facebook, Twitter and recently also Instagram introduced algorithms to function as gatekeepers. Brand messages only pop up onto one's timeline when messages are identified as potentially relevant for that person, to ensure that people receive content people actually care about. As brand posts, in general, are considered less relevant than user-generated messages, only a small percentage of the brand's fan base will have an opportunity to see its messages and share it with others. To open the gates of Facebook or Twitter's algorithms, brands (again) have to pay. Or, they need to offer the right content at the right moment to the right audience. Relevance is an important factor in social media algorithms (Agrawal, 2016).

So far, research has explored the effects of various content- and audience characteristics. This body of literature has enhanced our understanding of social media marketing. For example, Suh et al. (2010) show that individuals are more likely to pass along messages when they score highly on opinion leadership. Others show that individuals are more likely to engage in online word of mouth when they are motivated by a desire to help other consumers, or driven by social benefits of sharing information. Type of content is also pivotal for driving post success. Yuki (2015) shows that posts that consists of informational content leads to sharing. This is also supported by Araujo et al. (2015), whom found that *informational* cues were

important predictors of re-Tweeting. Others find that entertaining posts instigate more shares than informational posts (Cvijikj & Michahelles, 2013).

Thus, various audience- and content characteristics have been examined to gain insight in the effectiveness of brand messages on social media. However, little is known about moment-related characteristics, and how they contribute to message sharing. What is the right moment to post content on social media? This question is pivotal considering the premise that brand posts increase in relevance, and thus shareability, when offered at a right moment. This study extends previous research by examining exactly this question.

Real-time social media marketing

More than ten years ago Kumar and colleagues (2006) already pointed out the importance of scheduling advertising to increase revenue. Posting time has increased in importance now timelines are overloaded with content from a variety of sources. This is also acknowledged by practitioners. However, only a handful of studies have examined timing as a driver of brand post success (for a review, see Sabate et al., 2014). For example, the day and time of publication determines click-through rates (Rutz and Bucklin, 2011). Moreover, Cvjikj and Michahelles (2013) showed that posting during workdays increases word of mouth, especially when making use of so called “low hours” (between 4 a.m. and 4 p.m.).

To gain momentum, practitioners do not only think in terms of timing, but also in terms of moments. Brands increasingly link content with moments or events that are highly discussed on social media. Joining conversations by aligning or associating brand messages with publicly discussed events is also known as real-time marketing (RTM). RTM is a promising strategy for three reasons. First, RTM matches with consumers’ social media experiences. According to a recent study by Voorveld (2016), consumers mostly use social media such as Facebook or Twitter to interact with others, and keep up with current events and new developments (actuality). Second, the algorithms of Facebook and Twitter allow content to appear on people’s timelines when identified as “relevant”. Content is considered relevant when it aligns with discussions that are already taking place (Forbes, 2016). Third, studies show that social media users adapt their communication behavior to anticipated audience interest. Hence, consumers are more likely to pass along or forward content on social media, when it is believed to be publicly relevant.

Because of these potential benefits, RTM is a common practice. This is reflected by the heavy use of so called “content calendars”. Content calendars list moments and events that are expected to garner public attention so that brands can plan the creation and publication process of RTM. The rationale underlying the use of content calendars is that moments such as holidays (e.g. Christmas) or public events (e.g. Olympic Games) are relevant for a wide and diverse public, and have a leveraging effect for brand posts.

RTM is not a new phenomenon. Even before the introduction of social media, brands linked traditional media messages with public events. As already noted by Sutherland in 1997, it creates “[...] *opportunities to hitch a ride and harness the brand to something that will help move it more effortlessly and drive its budget further*”. However, unlike traditional media, social media allow real-time communication and as such enables brands to link their content to predictable events, but also events that simply happen and could not be predicted in advance (Kerns, 2014). As such, they can take-up trending topics (e.g., Pokemon Go and #thedress), and use it in their advantage to obtain viral status. Unpredictability, and related concepts such as unexpectedness and surprise, are found to be drivers of word of mouth behaviour (Berger & Milkman, 2012; Rudat et al., 2014). Thus, brands could boost the effects of RTM when aligning their messages with unpredictable public events.

To the best of our knowledge, no academic research has been undertaken to examine the use of RTM on social media, and test advertisers’ assumptions about the effectiveness of various

RTM strategies on social media. We expect that, when making use of RTM on social media, brands are more likely to align social media messages with predictable events (vs. unpredictable events), as they allow brands to plan the creation and publication process (H1). Moreover, based on the literature, we argue that RTM messages elicit more sharing behaviour than messages that do not make use of RTM (H2a), especially when RTM messages are aligned with unpredictable moments (H2b).

STUDY 1

The aim of study 1 was to examine the use of RTM as a strategy to boost the sharing of brand messages on social media. To address this aim, we performed a content analysis of brand messages, as posted on Twitter by the top-100 Dutch advertisers, composed by Nielsen in 2016. We selected brands from Nielsen's the Top-100 advertisers as this ranking (1) covers brands that score highly on gross media spending to minimize variations in brand familiarity, and (2) covers brands from 10 different market segments to increase the generalizability of the results (cf. Araujo et al., 2015). We randomly selected three brands per market segment, resulting in 30 brands in total. For each of these brands, we collected the names of their Twitter profiles. Twitter accounts were selected when they were verified as an official brand profile. In case a brand owned various Twitter profiles that matched these criteria, we selected those that were used for marketing communication purposes. Brand messages were obtained by using a social media monitor, Obi4wan, which collected all tweets from selected brands as posted between June 1st, 2015 and December 1st, 2016. To ensure equal group sizes, tweets were subjected to a stratified random sampling method, with brand name as stratum. This procedure resulted in a sample of 1500 unique tweets equally distributed over brands (n = 50 per brand).

The data was manually coded by two coders. Coders were trained over the course of two weeks to apply a coding instrument that was developed based on literature and pilot tests. The coding instrument included instructions to identify the presence of RTM techniques in Twitter posts from brands. As part of the training, coders coded a subsample of tweets that was not included in analyses to determine inter-coder reliability (n = 150, 10 % of the sample).

Measures

Sharing behavior. The dependent variable was the number of retweets that each brand tweet obtained. To guarantee a normal distribution of the residuals, we used natural logarithms, being calculated as $\text{LN}(\text{retweets}+1)$ (cf. Sabate, 2014) (M = 3,60, SD = 14.68; min = 0; max = 308).

RTM. To identify RTM in brand tweets, coders determined whether a message was aligned or associated with a public event (0=no; 1=yes, see: Kerns, 2014). Krippendorff's $\alpha = 1.00$.

Predictability of the event. In case a brand message could be identified as RTM, coders determined whether the event was predictable (e.g. public holidays, season related, events that are usually mentioned on a content calendar), or unpredictable (e.g. unexpected trending topics like #thedress or Pokemon Go, content that could not be planned in advance).

Krippendorff's $\alpha = 0.84$

Covariate. RTM in brand tweets often comes with visual imagery such as photos or videos. The presence of such material is a found to be a strong predictor of sharing behavior, and therefore included as a covariate (Araujo et al., 2015).

Analyses

Analyses showed that RTM was a common strategy; 19,6% of the brand messages were associated with events. A small percentage of these messages were replies to individuals,

rather than posts targeted at a general public. When leaving out individually targeted messages, 17% of the brand messages could be seen as RTM messages.

We predicted that brands are more likely to link their tweets with predictable events than with unpredictable events (H1). This hypothesis was supported by the data. Predictable RTM ($n = 201$, 13%) was far more common than unpredictable RTM ($n = 67$, 4.4%). These proportions differed significantly ($Z = -8.57$, $p < .001$).

Furthermore, we expected that brand messages that are associated with public events elicit more shares than brand messages that are not associated with public events, especially when events occur unpredictably (H2a/b). To test these hypotheses we employed multilevel regression, using a random intercept-fixed slope model. Allowing random effects on intercepts is recommended to reduce the variance caused by variables on the second level (Cohen et al., 2013), which in this study was the brand level. This procedure was selected as certain brands may prompt more retweets than others because of differences in popularity or the size of the fanbase. To compare predictable and unpredictable RTM with brand tweets that do not make use of RTM, we created $k-1$ dummies, with no RTM as a reference category (Cohen et al., 2013). This resulted in two dichotomous variables, one comparing brand tweets that contained predictable real time marketing with brand tweets that contained no RTM, and a second comparing brand tweets that contained unpredictable RTM with brand tweets that contained no RTM.

The results in table 1 showed that, when controlling for the effects of visual imagery, no significant relation was found when no RTM was compared with predictable RTM ($b = .09$, $p = .173$). However, we did find a significant relation when making the comparison with unpredictable RTM ($b = .29$, $p < .01$). Brand tweets that contain RTM are more likely to be shared (vs. brand tweets that do not contain RTM) when those tweets are linked with an unpredictable public event, but not when linked with a predictable public event. This finding provides partial support for H2.

STUDY 2

The first study shows that RTM occurs less often in response to unpredictable events than predictable events. However, RTM is only more successful than brand messages that do not use RTM, when messages are associated with unpredictable events. The second study extends study 1 by examining content characteristics that could possibly improve the effects of predictable RTM. Under the premise that RTM is successful when making a link to public events, we expect that predictable RTM will stimulate forwarding behavior when it makes this link explicit. This can be done in at least two ways.

First, predictable RTM can make use of event-driven hashtags (Kerns, 2014); i.e., hashtags that make a reference to a public event. Hashtags are implemented in social media to assign topics to posts, and as such make content searchable (Boyd et al, 2010). As such, content becomes accessible to a larger public of social media users than those that belong to a brand's fan base. Thus, hashtags function as "conversational tagging" (Huang et al., 2009), thereby increasing "the ability to find what other people are talking about in real-time" (Boyd et al., 2010). Indeed, prior research confirms that hashtags increase sharing behavior (Araujo et al., 2015; Suh et al, 2010). Thus, we expect that the presence of event-driven hashtags in predictable RTM messages (vs. absence) yields more shares (H3).

Second, predictable RTM can gain in relevance when the event is integrated with the brand's message. As shown in study 1, RTM often comes with visual imagery. When an event is integrated in visual imagery, a brand can make a vivid connection with its surrounding context, i.e., the event. Research on brand placements provides initial support for this contention. Brand placements that are well-connected to the story lines editorial content, make brand messages less obtrusive and more relevant, and thus more effective (for a review,

see Balasubramanian et al., 2006). In the case of RTM, brand messages are not embedded in an editorial context (as with brand placements) but instead, the context is embedded in brand messages. Nevertheless, we argue that moment integration enables brands to become more relevant for its key public as it enables them to make a meaningful connection with the public. This is supported by research showing that meaningfulness or relevance is a strong driver of ad creativity effects. If a message does not fit with what is going on in the lives of consumers, ads are likely to be discounted (even when the ad is judged as being very original, for a discussion see White et al., 2002). Thus, based on the literature, we propose that predictable RTM messages yield more retweets when public events are integrated in visual imagery (vs. not integrated) (H4).

Method

Study 2 explored whether moment-driven hashtags and moment integration (H3 and H4) may increase the effects of predictable RTM. To examine these effects, we employed a content analysis of RTM messages, as posted on Twitter by the Forbes Top-100 brands in 2016. As RTM involves the process of associating or aligning brand messages with events that garner public interest, we collected brand messages that were posted in relation to three public events that could be planned in advance: Christmas, Valentine's day, and the Star Wars premiere. Christmas and Valentine's day were selected as public holidays garner attention from a wide and diverse audience, and are therefore highly discussed on social media such as Twitter (Kent, 2014). The Star Wars premiere was selected as this event was mentioned on several content calendars, and was one of the most often discussed moments in 2016 according to Twitter's year in review (Twitter, 2016).

Brand messages were obtained by means of Twitter's search advanced tool, with a query that collected all tweets that had been published by selected brand profiles three months before each event until three months after the event. This yielded 1017 tweets. We selected 50 random tweets per moment. Tweets were only kept in the sample when they consisted of original posts (thus leaving out replies and retweets) and matched with the definition of RTM. The final sample consisted of 143 RTM messages.

Real-time messages were manually coded by students that were trained and supervised during a marketing course. Students followed the instructions of a coding instrument that was developed based on literature and pre-tests (see measures). A random sample (18%) was assessed by an additional coder to determine inter-coder reliability.

Measures

Sharing behavior. The dependent variable was the number of retweets that each brand tweet obtained. These numbers were automatically retrieved by means of Twitter's advanced search tool. The dependent variable was log transformed as $\text{LN}(\text{retweets}+1)$, as the distribution of retweets was found to be skewed ($M = 154,13$, $SD = 330,332$; $\text{min} = 0$; $\text{max} = 2117$).

Presence of moment-driven hashtags. By means of manual coding, we determined whether real-time messages were linked to the event through moment driven hashtags (0=no; 1=yes); that is: hashtags that make any reference to the event (e.g., #starwars; #TheForceAwakens, #showusyourforce). Krippendorff's $\alpha = .87$.

Moment integration. Coders determined whether the event was visually depicted and integrated in the brand message (0=no; 1=yes). Krippendorff's $\alpha = .84$.

Covariates. To control for differential effects emerging from individual events, we created two dummies, each using Christmas as reference category. In addition, we included the natural log transformation of brand equity as a covariate to control for brand effects. Brand equity figures were expressed in billions of dollars and obtained from the Forbes top-100 list.

Results

The results showed that RTM is a popular social media strategy: 61% of all brands had posted one or more RTM messages in relation to these three selected events. Furthermore, 51% of RTM messages contained a moment-driven hashtag. Moreover, 94% of the RTM messages contained visual imagery¹, and 66% of these posts integrated the moment in visual imagery. When controlling for these individual events, and each brand's monetary value, multi-level analyses revealed no significant relation between moment-driven hashtags and sharing behavior ($B = 0,13, p = .51$). The presence of such traceability cues were not found to boost the sharing of predictable RTM messages. Hence, H3 could be rejected. However, the results did provide support for H4, which predicted a positive relation between moment integration and sharing behavior. As shown in table 2 brand tweets in which predictable events were visually integrated yielded more retweets than brand tweets in which predictable events were not visually integrated into the message ($B = 0,38, p = .05$).

CONCLUSION

Twitter timelines are increasingly populated with brand tweets that are linked to public events, a practice that is also known as real-time marketing (RTM). In two studies, we examined whether RTM is an effective strategy to boost sharing behavior, and if so, what event- and content-related characteristics are likely to contribute to its effectiveness. The first study involved a content analysis of brand tweets from Nielsen's top-100 advertisers ($n=1500$). These findings contribute to the literature on RTM as this study was the first to demonstrate impact of aligning brand messages on social media with public events. As such it provides evidence-based support for RTM as an advertising strategy to boost shareability of brand messages on social media. However, it also shows that not all events are equally effective. RTM is only a more effective strategy (vs. no RTM), when brand messages are linked with unpredictable events but not when brand messages are linked with predictable events.

In a follow-up study, we examined what content characteristics improve the shareability of predictable RTM messages. A content analysis of RTM messages from the Forbes top-100 brands showed that predictable events yield more shares when the event is visually integrated in the brand tweet (vs. not visually integrated). Brands benefit from embedding a surrounding context into their messages, as demonstrated by increased numbers of shares when predictable events are visually integrated into brand messages. Providing a visual connection in the execution of RTM messages, enables brands to capitalize on predictable public events. This finding contributes to the literature on context effect that has mostly examined situations in which brand messages are embedded in editorial contexts (e.g., brand placements).

Against expectations, the presence of event-driven hashtags did not lead to more shares. This suggests that in the case of RTM, hashtags may not always serve as searchable content (Araujo et al., 2015; Boyed et al., 2010), but more as signals that mark experiential topics (Zappavigna, 2015). Further research is undertaken to examine whether similar effects for moment integration and hashtags can be found for unpredictable events. Further research is also recommended to isolate the effects of moment characteristics and content characteristics in a controlled setting, and whether perceived relevance serves as an underlying mechanism for these effects.

¹ Leaving out messages without visual imagery in the analysis did not lead to different results.

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APPENDIX

Table 1. Multilevel regression analysis for retweets (study 1)

	<i>B</i>	SE B	<i>p</i>
<i>Fixed effects</i>			
intercept	0,73	,07	,000
Visual imagery	0,40	,02	,000***
RTM (RTM)			
Predictable RTM vs. no RTM	0,09	,06	,173
Unpredictable RTM vs. no RTM	0,29	,11	,006**
<i>Random parameters</i>			
Variance of intercept	0,14	,02	,000***
Variance of residual	0,60	,04	,000***
-2 Restricted log likelihood	3431,98		

Table 2. Multilevel regression analysis for retweets (study 2)

	<i>B</i>	SE B	<i>p</i>
<i>Fixed effects</i>			
intercept	0,83	,83	,312
Brand value	1,03	,29	,001***
Type of event (Christmas = ref)			
Valentines day	0,06	,26	,819
Starwars premiere	-0,29	,20	,276
Content characteristics			
Event-driven hashtag	0,13	,06	,513
Moment integration	0,38	,19	,05*
<i>Random parameters</i>			
Variance of intercept	1,59	,37	,000***
Variance of residual	0,62	,09	,000***
-2 Restricted log likelihood	435,86		