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# 'Retweet for a Chance to…': an analysis of what triggers consumers to engage in seeded eWOM on Twitter

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**ABSTRACT**
Twitter provides an important channel for brands to seed electronic word of mouth (eWOM) by followers retweeting brand messages, but prior research has not established a theoretical framework for how brands can maximise eWOM. This study presents and tests a theoretical model incorporating interactive, textual and visual tweet features to predict eWOM, using tweets by leading brands from three industries. Industry was found to be an important moderator of the effect of tweet features; after controlling for the reach and frequency of tweets, hashtags, retweet requests and photos were consistently associated with a higher retweet rate across industries, but the effect of URL links, non-initial mentions and video varied across industries, in some cases decreasing the retweet rate. Implications for research and practice are discussed.

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## Introduction

Social media have been said to be a 'game changer' for industries, influencing companies to increase their social media budgets to promote their brands (Kumar, 2015). Brands are expected to spend almost $35.9 billion worldwide on social media in 2017, representing 16% of their total digital expenditure (eMarketer, 2015). Part of the reason for this large spending on social media is the potential that social media offer for creating viral marketing recommendations from consumer to consumer, but achieving this goal is often elusive (Schulze, Schöler, & Skiera, 2014).

Among different social media platforms, existing research has highlighted that Twitter provides opportunities for marketers to facilitate consumer-to-consumer brand-related conversations due to its focus on sharing information and facilitating discussion (e.g. Canhoto & Clark, 2013; Smith, Fischer, & Yongjian, 2012). Brands can send tweets to their followers, with the aim that the messages will be sufficiently engaging for those followers to forward (or 'retweet') them to their own networks. Retweeting is an important activity on Twitter as it facilitates virality and the spread of real-time information (Rudat & Buder, 2015). However, there appear to be wide differences in consumer engagement with tweets between industries and between brands, with even leading brands in some industries having very low retweet rates

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(Soboleva, Burton, & Khan, 2015). Thus, it is important for both marketers and academics to better understand how various tweet features facilitate propagation of brand messages, whether there are significant differences between industries, and how brands can best influence consumers to forward brand messages to their own networks.

In this paper, we analyse a sample of 13,712 tweets from 32 leading global brands in three different industries (Automotive, FMCG and Luxury) to examine the factors that predict retweeting of brand messages. We test to what extent the inclusion of interactive, textual and visual features in tweets is associated with the frequency of retweeting brand messages.

The paper is structured as follows. First, we review the literature on electronic word of mouth (eWOM), its importance for marketers, and how social media and, in particular, Twitter overcome two of the main challenges for marketers in using eWOM as a marketing tool. Second, drawing on previous research in interactive marketing and advertising in the context of crafting viral tweets, we develop a theoretical framework depicting the factors that are theorised to increase consumer engagement with brand tweets, as demonstrated by retweeting those tweets. Third, we describe our data collection and analysis approach. Finally, we present the results of our analysis and discuss the implications for organisations' Twitter strategies and for research.

## Theoretical framework

### *The power of eWOM in the age of social media*

Word of mouth (WOM) has long been of interest to marketers, due to its influence on customer behaviour and choices (e.g. Brown & Reingen, 1987; Engel, Blackwell, & Kegerreis, 1969). WOM is perceived as more authentic, less biased, and thus has higher credibility than advertising messages (e.g. Bristor, 1990; Keller, 2007). However, organisations have often struggled to systematically manage WOM because it is often generated by factors beyond firms' control (Haywood, 1989). In addition, the difficulty of measuring face-to-face WOM adds to the challenges in using WOM for marketing (Christiansen & Tax, 2000).

The advent of online communication channels such as Web-based opinion platforms increased the interest of marketers in online or electronic word of mouth (oWOM or eWOM) (e.g. Chevalier & Mayzlin, 2006; Hennig-Thurau, Gwinner, Walsh, & Gremler, 2004). Before the advent of social media, eWOM was defined as:

> any positive or negative statement made by potential, actual, or former customers about a product or company, which is made available to a multitude of people and institutions via the Internet. (Hennig-Thurau et al., 2004, p. 39)

Since that period, however, advances in digital technology in the past decade have vastly increased both the ways in which eWOM can be transmitted, and its importance as a marketing channel. In response, research into oWOM/eWOM has progressed from a focus on 'legacy' forms of eWOM, such as consumer statements through product ratings and reviews, to incorporate newer forms of eWOM such as engaging on social media platforms (e.g. by likes, comments, shares, retweets and favourites) (Lamberton & Stephen, 2016). Although such eWOM often does not include the 'statement' reflected in the classic definition of eWOM, these newer forms of eWOM provide a measurable record that is available for the researcher or marketer (e.g. Dellarocas & Narayan, 2006; Kozinets, de Valck, Wojnicki, & Wilner, 2010), thus addressing one of the major challenges to using WOM for marketing discussed above.

However, consumer-initiated eWOM, whether on Web-based opinion platforms or on newer forms of social media, reflects the challenge of spoken WOM discussed above in being difficult or impossible for the marketer to manage, because the source of the eWOM is the consumer. Most early studies of eWOM focused on this type of consumer initiated (or peer-to-peer) eWOM (e.g. Fong & Burton, 2006; Godes & Mayzlin, 2004). Such studies do not reflect, however, that eWOM can be created either through opinion *giving* or opinion *passing* (Chu & Kim, 2011). That is, an individual can initiate WOM by transmitting their opinions to others, or pass on WOM received from others. There has been repeated discussion in the literature consistent with this expanded conceptualisation of eWOM (e.g. Araujo, Neijens, & Vliegenthart, 2016; Chu, Chen, & Sung, 2015; Kim, Sung, & Kang, 2014; Rosario, Sotgiu, De Valck, & Bijmolt, 2016; Zhang, Jansen, & Chowdhury, 2011). However, surprisingly, we have not found an updated definition of eWOM reflecting its use for opinion passing, as well as opinion giving. Building on both Hennig-Thurau's et al. (2004) definition of eWOM and Chu and Kim's (2011) conceptualisation of eWOM on social networking sites, we therefore propose an updated definition of eWOM to incorporate its expanded use in the age of social media:

> a process by which potential, actual or former customers give or pass on an opinion or statement about a product or company, which is made available online, potentially to a multitude of people and institutions.

The potential for consumers to engage in favourable eWOM on social media by passing on messages, therefore, presents an opportunity for organisations, which can create communications in an attempt to encourage eWOM by using what have been called 'seeding' strategies (e.g. Godes & Mayzlin, 2009; Hinz, Skiera, Barrot, & Becker, 2011; Koch & Benlian, 2015). The earliest form of such 'seeded' eWOM was probably email marketing, where an organisation's message, either implicitly or explicitly, encouraged the recipient to forward the email to their contacts. Pass-along of email messages and its measurement is, however, limited by the private nature of email. In contrast, the emergence of social media platforms such as Facebook, Twitter and LinkedIn, where users are easily able to create and forward brand- related information to their networks (Vollmer & Precourt, 2008), has vastly increased the potential reach and measurability of eWOM – including the dissemination of tweets originating from firms (e.g. Hewett, Rand, Rust, & van Heerde, 2016). So organisations can initiate or 'seed' eWOM on social media and measure its dissemination – thereby providing the opportunity to identify the characteristics of messages which are widely disseminated or 'go viral', as we discuss in the following section.

### *Retweeting as a measure of eWOM on Twitter*

Among social media platforms, Twitter is particularly appropriate for seeding eWOM because users subscribe to messages from other users, including those by commercial organisations, and can also view a brand's posts without following the organisation. In addition, sharing others' posts, or 'retweeting' is easy – requiring only one click – and retweeting others' content is normal behaviour on Twitter.

So, if a brand's followers find that the brand's tweets are sufficiently engaging, they can retweet messages to their own networks, creating eWOM in the form of tweets (e.g. Williams, Inversini, Buhalis, & Ferdinand, 2015; Zhang et al., 2011). (While it is technically possible to retweet a brand message with critical commentary, Twitter's character length, and the observed association between retweeting and positive brand evaluations (Kim et al., 2014), retweets are likely to largely reflect positive, or at least neutral, eWOM.) Retweeting of brand tweets is, therefore, an important measure of the success of a brand in generating eWOM on Twitter, as WOM disseminates across Twitter through retweets (Walker, Baines, Dimitriu, & Macdonald, 2017). Thus, understanding the factors that increase (or decrease) the probability of a message being retweeted is critical for effective marketing on Twitter. In the next section, we present a theoretical model summarising the factors that are expected to increase the probability that a message will be retweeted.

### *What predicts retweeting? A theoretical model*

While Twitter is a relatively recent phenomenon, there is an emerging body of empirical research exploring tweet features that are associated with higher retweet rates (e.g. Araujo, Neijens, & Vliegenthart, 2015; Malhotra, Malhotra, & See, 2012; Suh, Hong, Pirolli, & Chi, 2010). Such research, however, lacks a unifying theoretical model to explain why different tweet features may increase (or decrease) retweeting. However, there is a large body of research into advertising effectiveness that is relevant for identifying factors that may influence the effectiveness of Twitter communications. Drawing on both these fields of literature, we first develop a theoretical model of factors that are likely to drive consumer engagement with brand tweets, operationalised as the frequency of retweeting (see Figure 1), and then go on to test that model. In the next section, we review each of these factors separately, as well as control variables that are relevant for the study.

## Consumer involvement with the product category

Consumers' interest in retweeting a brand tweet is likely to depend on their involvement with the brand and/or product category and/or message, following past research that reported product and message involvement were two of the main motivations for consumers to talk about a product or service (Dichter, 1966). Consistent with that research, one study has found that product involvement (in the form of fashion involvement) and brand involvement are the key motivators for eWOM by consumers (Wolny & Mueller, 2013). In a social media environment, consumer involvement appears to influence reactions to promotional messages, with lowly involved consumers being particularly drawn to entertainment content, and highly involved consumers responding more to informational messages (Coursaris, van Osch, Balogh, & Quilliam, 2014).

Consistent with the potential importance of involvement for moderating consumer responses to brand messages discussed above, this study examines retweeting of tweets from leading brands in three different industries. One of the industries represents FMCG

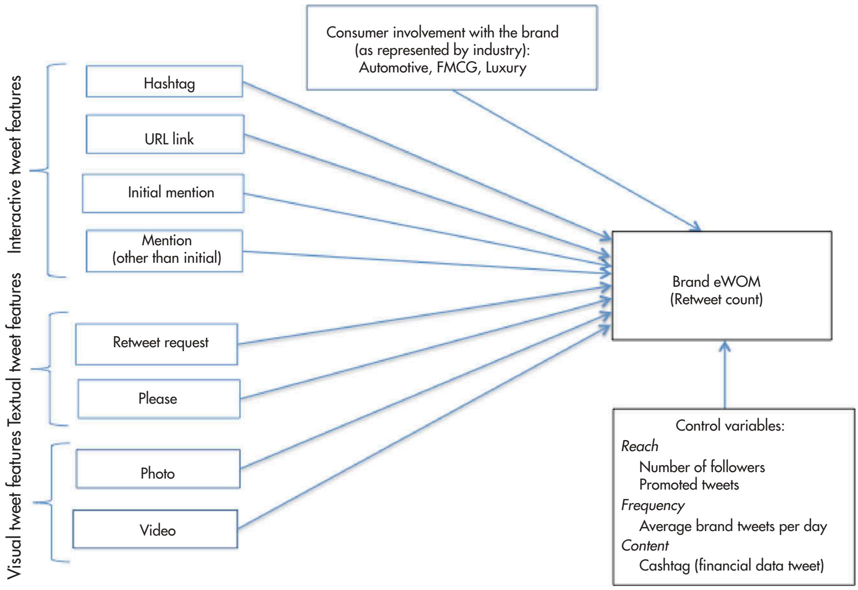


**Figure 1.** Engagement mechanisms that facilitate retweeting behaviour.

(CPG) companies, a low-involvement product category, since the products are low risk and not very important to the consumer (Silayoi & Speece, 2004). The other two – Luxury and Automobiles – represent high-involvement products, since the products relate strongly to self-representation and are infrequently purchased (Vigneron & Johnson, 1999). Thus, Figure 1 models a consumer's likelihood of retweeting a brand message as varying according to the consumer's level of involvement, as represented by industries offering high- and low-involvement products.

## Interactivity of Twitter messages

Interactivity has been an area of focus for marketers for at least 20 years (e.g. Duncan & Moriarty, 1998; Hoffman & Novak, 1996), because interactivity can increase consumer attention and flow (Hoffman & Novak, 1996), and forms the basis of long-term two-way relationships with customers (Duncan & Moriarty, 1998). Although there are different definitions of interactivity (Hui & Nadda, 2014), one widely cited source defines interactivity as 'the extent to which users can participate in modifying the messages they receive' (Steuer, 1992, p. 84). Building on Steuer's definition, Hoffman and Novak (1996) argued that computer mediated environments (such as Twitter, though they were writing before the advent of Twitter) can allow interactivity *with* the medium (which they called 'machine interactivity') in addition to *through* a medium (which they called 'person interactivity'). While Twitter, like all social media, allows person interactivity, different Twitter design features encourage Twitter followers to interact with the medium, for example, by clicking on an embedded hyperlink in a tweet. In this study, we extend Hoffman and Novak's analysis, by analysing the extent to which interactive and other tweet features increase consumer engagement with tweets, as measured by the frequency of retweeting. Interactive features of tweets represent the first group of mechanisms to facilitate retweeting behaviour shown in Figure 1, and in the following section, we discuss each separately.

### *Hashtags*

The use of hashtags linked to keywords in tweets (e.g. #xmasdeals) enables users to discover and follow tweets containing the same hashtag, and can therefore improve content discovery (Huang, Thornton, & Efthimiadis, 2010). The presence of a hashtag in a tweet is thus an example of machine interactivity because such a tweet has a greater probability of being found by individuals who do not follow the tweet's sender, but who are sufficiently interested in the hashtag's topic to search for tweets containing that hashtag. Possibly because the use of a hashtag means that a larger number of people see the tweet, the inclusion of a hashtag in a tweet has been found to increase the retweet rate (Burton & Soboleva, 2011; Suh et al., 2010). One recent estimate found that inclusion of a hashtag increases the retweet rate by 46% (Kerns, 2014). However, the effect of including one or more hashtags in a tweet may be non-linear: another study found that tweets containing one to three hashtags are more likely to be retweeted than tweets without hashtags, but as the number of hashtags in a tweet grew, the average number of retweets decreased (Jenders, Kasneci, & Naumann, 2013). Thus, Figure 1 models hashtags in a tweet as increasing the probability of retweeting, but the model tested also includes a squared and a cubic term to test for a non-linear effect of hashtags on retweeting.

### *URL links*

Inclusion of a URL link in a tweet, thereby providing users with access to extra information, is another example of machine interactivity (Burton & Soboleva, 2011). For example, URL links are said to increase interactivity of websites (Fortin & Dholakia, 2005) and social media brand posts (de Vries, Gensler, & Leeflang, 2012). Hyperlinked tweets are considered more informative (Sedhai & Sun, 2014) and are likely to be more interesting (Alonso, Carson, Gerster, Ji, & Nabar, 2010). These presumed effects may explain repeated findings that tweets with URL links, on average, are retweeted more often (e.g. Naveed, Gottron, Kunegis, & Alhadi, 2011; Son, Lee, & Kim, 2013; Suh et al., 2010). In contrast, however, two other studies have reported that inclusion of a URL did not increase retweeting (Malhotra et al., 2012; Saxton, Niyirora, Guo, & Waters, 2015), suggesting that the effect of URL links may be less clear-cut than has been suggested by previous literature. In line with most findings in this area, however, Figure 1 models the presence of a URL link as being associated with the probability of retweeting.

### *Mentions and initial mentions*

Mentioning others in a tweet is another form of interactivity; by mentioning others, the interpersonal interactivity of the tweet is increased (Burton & Soboleva, 2011) – primarily for mentioned users, but also for any other users who are interested in the mentioned users (for example, people who follow mentioned celebrities). Mentions are also, however, a form of machine interactivity, since including a mention in a tweet results in the tweet being automatically sent to the person or brand Twitter handle. Consistent with this possibility, previous authors have examined the effect of mentions on retweet count and found varying results: either no effect of mentions on retweeting (Petrovic, Osborne, & Lavrenko, 2011), a marginal negative effect (Suh et al., 2010) or a significant negative effect (Tan, Lee, & Pang, 2014).

However, the effect of a mention may depend on whether it is at the start of a tweet (i.e. an 'initial mention tweet'), or elsewhere within the tweet. For example, research studying linguistic and interactional features of an earlier online communication channel – internet relay chat (Werry, 1996) – has discussed the value of using a person's name at the beginning of an utterance to capture the addressee's attention, in a way that a reference (or, on Twitter, a mention) later in the message may not achieve. Drawing on Werry's research, an initial mention tweet thus accomplishes what has been called 'addressivity' (Honeycutt & Herring, 2009). As well as capturing the attention of a mentioned person (or brand) as discussed above, a mention at the start of a tweet may also capture the attention of others, if the mentioned person (or brand) is of sufficient interest, thus potentially resulting in an increased number of retweets. For instance, recent research has shown that tweets are more likely to be retweeted if they have been retweeted by an influential person, such as a celebrity (e.g. Araujo et al., 2016). Consistent with this logic, Figure 1 models a tweet that starts with an initial mention as having a higher probability of being retweeted relative to tweets without an initial mention.

A mention elsewhere in a tweet, while lacking the addressivity of an initial mention tweet, is also likely to draw the attention of the mentioned person (or brand), thus potentially resulting in them retweeting the message, and potential retweets by their followers, albeit a smaller increase than may be achieved by an initial mention tweet if addressivity is important. Thus, Figure 1 proposes that the presence of a mention elsewhere in a tweet will influence the retweet rate. However, consistent with both the theoretical potential for mentions to increase retweets, and with previous reports of both negative and/or absent effects of mentions on retweets, as discussed earlier, the direction of effect is uncertain.

## Textual and visual Twitter features

Apart from the interactive tweet features discussed above, shown as the first group in Figure 1, the probability of retweeting is likely to depend on textual and visual features of the tweet, as shown in the second and third groups on the left in Figure 1. Just as a printed or web advertisement is typically a combination of design elements such as text and images, a carefully crafted brand tweet can combine linguistic features and imagery elements that may increase its virality. Figure 1, therefore, models the effect of different textual and visual tweet features, with each discussed separately below.

### *Retweet request*

A call to action is an advertising technique for increasing customer response that has been used for more than a century (e.g. Starch, 1914). The use of a clear call to action attracts attention and makes it easier for consumers to act on a specific request (Armstrong, 2010). For example, a call to action in SMS advertising has been shown to facilitate brand recall (Rettie, Grandcolas, & Deakins, 2005) and for display banner ads, significantly increase response (Chandon, Chtourou, & Fortin, 2003; Li & Bukovac, 1999). A retweet request within the text of a tweet is another form of call to action, which, following the research on calls to action in advertising, would be expected to increase retweeting. Consistent with this argument, other types of call to action (such as tweets soliciting the public's help) have been found to increase the number of retweets of nonprofits' tweets (Guidry, Waters, & Saxton, 2014). Since it calls on the tweet recipient to respond, a retweet request could be classified as an interactive tweet feature. However, the effectiveness of calls to action will always depend on the justification for the call, which in a tweet is encapsulated in text, and therefore best categorised as a textual tweet feature.

There are varying commercial studies of the effectiveness of direct appeals for retweeting, reporting increases in retweeting ranging from 34% with inclusion of a retweet request (Malhotra et al., 2012) to 1,200% (Salesforce, 2013). A retweet request may, however, be less effective for low-involvement brands/goods, since the subsequent step for action is obvious for these products (Armstrong, 2010). Consistent with the empirical evidence that inclusion of a retweet request increases retweeting, Figure 1 therefore models a retweet request as increasing the probability of retweeting, though possibly varying with the product type involved (i.e. low or high involvement).

### *Using the word 'please' in tweets*

The study also tests the effect of a more subtle request, as expressed by the word 'please', since a polite request may receive more attention and subsequent action than an assertive request (Forgas, 1998). Polite requestors have higher potential to receive a response in line with politeness theory, which indicates that speakers generally choose more polite strategies to mitigate the seriousness of their request (Brown & Levinson, 1978). Polite requests asking customers to engage in WOM activity have also been shown to increase WOM (Söderlund & Mattsson, 2015), with one study on Twitter demonstrating a positive impact of the use of word 'please' on retweets (Tan et al., 2014). Some researchers recommend companies use polite requests to retweet their messages in order to increase engagement by users and customers (Malhotra et al., 2012). Thus, Figure 1 proposes that the presence of the word 'please' in a tweet will be associated with a higher retweet rate.

### *Photos in tweets*

In addition to the textual tweet features discussed above, the probability of a tweet being retweeted is likely to depend on visual tweet features. For example, a substantial body of research has shown that pictures can increase the effect of advertisements, in part, because pictures can project meanings that cannot be expressed via words or music (Messaris, 1996). In print advertising, both the size and the colour of pictures have been found to influence overall affect towards the brand (Percy & Rossiter, 1983). Images can also improve recall of the verbal information of the ad (e.g. Unnava & Burnkrant, 1991), increase the potential for attitude change (Rossiter & Percy, 1980) and influence consumer persuasion (e.g. McQuarrie & Phillips, 2005). In social media, vividness (which can be represented by animations, contrasting colours or pictures) can enhance the number of likes of a Facebook brand post (de Vries et al., 2012). Conflicting evidence exists on the effect of images in tweets, with one study finding that tweets with photo links do not impact retweetability (Malhotra et al., 2012) and another reporting that tweets with links to photos are retweeted more than twice as much compared to tweets without such links (Bruni, Francalanci, & Giacomazzi, 2012). Therefore, Figure 1 models photos in tweets as increasing the probability of retweeting. However, users have the option to include more than one photo in a tweet, and it is not clear whether including more than one photo will increase the frequency of retweeting (by providing additional content), or decrease retweeting (due to increased visual complexity in the message). The model therefore tests for a non-linear effect of an increased number of pictures in a tweet.

### *Videos in tweets*

Until recently, to provide access to video (or photos) a tweet needed to include a URL link that a user could click on to view the video (or photo). However, since late 2013, Twitter allows users to embed videos (and photos), so instead of the user having to leave Twitter, the tweet itself expands to show the content (Cooper, 2013).

Although embedded video is relatively new on Twitter, earlier advertising research may be relevant for predicting its effect. In web advertisements, animated banner ads appear to increase click-through intention and advertising recall (Yoo, Kihan, & Stout, 2004). The popularity of videos is likely to be because they tap into fundamental human feelings; one study found that surprise and joy were dominant emotions in the most successful viral videos (Dafonte-Gomez, 2015). Videos on Twitter have been shown to enhance the richness of content and help marketers with different tasks from promotion to problem resolution (Leek, Canning, & Houghton, 2016). Twitter users may thus be more likely to retweet tweets containing video content. As with photos, Figure 1 therefore proposes that the presence of video in a tweet will be associated with a higher retweet rate.

## Control variables

### *Reach*

The probability of a tweet being retweeted is likely to depend, in part, on how many users the tweet reaches, because if more people receive the tweet, there are more people who can retweet it. The number of followers is thus an indicator of a Twitter handle's reach (Kwak, Lee, Park, & Moon, 2010), though it does not reflect the increased reach that will be achieved if those followers retweet the message.

Brands can also increase the reach of a tweet using 'promoted tweets', an advertising option that allows users (such as brands) to pay for tweets to appear in the feeds of users, including those who do not follow the brand. Such an approach exposes a promoted tweet to a larger number of people who can potentially retweet it. Promoted tweets can generate engagement and positive sentiment for brands

(Dacres, Haddadi, & Purver, 2013), but because they are labelled as promoted tweets, can discourage customers from further engagement or interaction (Wood & Burkhalter, 2014). Given the importance of the number of followers and the potential for a brand to increase the reach of a tweet by promoting it, the model tested therefore includes both number of followers and tweet promotion (no/yes) as control variables.

### *Frequency*

The retweet rate of a brand's tweets may also depend on how often the brand posts on Twitter. One study examined brands' creative strategies on Twitter, Facebook and other social sharing platforms and found that frequent updates and incentives for participation are important for customer engagement (Ashley & Tuten, 2015). Another study suggested that organisations can be considered active if they tweet at least three times per week (Lovejoy, Waters, & Saxton, 2012), although other researchers have found that to keep consumer engagement, tweets need to be updated every 24 h (Rybalko & Seltzer, 2010). It is likely, however, that only some minimum level of Twitter activity may be necessary; one study of 13 companies found that posting more tweets per day was not associated with a higher level of retweets (Mamic & Almaraz, 2013). The tested model, therefore, includes the average number of tweets sent by a brand each day as a control variable, and includes a square term to capture the assumed non-linear effects of frequency of tweeting.

### *Content*

A 'cashtag' is made up of a company's ticker symbol, preceded by a dollar sign (e.g. $TWTR for Twitter) and as with a hashtag, a user can click on a cashtag to find other tweets containing the same cashtag. There are only a small number of tweets that contain cashtags, but the financial data that are available from these tweets provides insights into stocks and companies (Hentschel & Alonso, 2014). Being information rich, tweets containing cashtags may be of little interest to consumers who do not value task-oriented content, and as a consequence they may be retweeted less often, consistent with research that has found that task-oriented messages are retweeted less frequently than socioemotional messages (Lin & Peña, 2011). Figure 1 thus models the presence of a cashtag in a tweet as a control variable, and associated with a lower retweet rate.

## Method

### *Sample and data collection*

Brands for analysis were chosen from Interbrand's Best Global Brands report (Interbrand, 2013). Since the interest of the study was in consumer response to organisational tweets, three B2C industries were chosen for analysis, including one low-involvement product category (FMCG), and two high-involvement product categories (Automotive and Luxury).

All brands on the Interbrand list within the three selected industries had Twitter handles except for one luxury brand (Hermes), resulting in a sample of 11 FMCG brands, 14 Automotive and 7 Luxury brands. Many companies have more than one Twitter handle, so the central organisational handle (and in the absence of an obvious central handle, the one with the largest number of followers) was chosen for analysis, consistent with Araujo et al. (2016). One FMCG brand, (Heinz), was excluded due to very low Twitter activity during the study period. Despite the relatively small number of brands within each industry category, the analysis therefore includes a Twitter handle from the entire population of active Twitter users among top-ranked brands in the three industries analysed. A list of all brands and Twitter handles examined is available in Appendix 1.

All tweets from the selected Twitter handles, and the retweet count for each tweet, were collected for a six-month period of 1 May 2014 to 30 October 2014 using Twitonomy's premium subscription service. This resulted in an initial sample of 38,756 tweets. However, 25,044 tweets were excluded from the analysis. The majority of tweets (21,221) were excluded because they were replies to other tweets, including 21,187 private replies, which are not sent to the sender's entire network, and so are likely to be retweeted less often. And 3,817 tweets were excluded because they were retweets by the examined brands (and the brand is therefore not credited with further retweets), and 6 were excluded because they were extreme outliers in the number of retweets, consistent with Araujo et al. (2016). The final sample size was, therefore, 13,712 tweets. Table 1 below provides a summary of the number of followers and tweets posted by each industry, after excluding outliers.



### Operationalisation of variables

Table 2 shows the operationalisation of the variables in the model and summary statistics. Tweets were coded for the presence and/or count of each independent variable using Excel formulas. There was wide variation in the use of different tweet features; hashtags and photos were the most widely used features, respectively, occurring in 65.4% and 57.9% of tweets. In contrast, cashtags, retweet requests and the word 'please' were rarely used, each occurring in less than 1% of tweets. The correlation matrix of the variables was reviewed, and did not demonstrate multicollinearity between the variables (see Appendix 2).

### Empirical model

The dependent variable – retweet count – is a count variable, thus it is most appropriate to use either Poisson or negative binomial regression. Initially, a Poisson distribution model was applied; however, the conditional variance of the dependent variable exceeded the mean, and the goodness-of-fit (chi-square) test was significant (suggesting overdispersion). The model was, therefore, tested using negative binomial

**Table 1.** Number of followers and tweets posted by industry after exclusions.

| | Auto ($n$ = 14) | | FMCG ($n$ = 11) | | Luxury ($n$ = 7) | | All ($n$ = 32) | |
|---|---|---|---|---|---|---|---|---|
| Industry (brands) | Mean | Std. Dev | Mean | Std. Dev | Mean | Std. Dev | Mean | Std. Dev |
| Followers per brand | 475,013 | 299,625 | 49,455 | 37,622 | 1,579,033 | 1,502,935 | 554,451 | 887,984 |
| Tweets posted per day per brand | 2.58 | 1.43 | 1.79 | 2.22 | 2.74 | 3.57 | 2.34 | 2.25 |

**Table 2.** Operationalisation of variables and summary statistics.

| Variable | Operationalisation | % of tweets | Mean | Std. Dev. |
|---|---|---|---|---|
| **Dependent variable** | | | | |
| RetweetCount | Number of retweets of each individual tweet (ranging from 0 to 6090) | n/a | 74.65 | 224.57 |
| **Independent variables** | | | | |
| **Interactive tweet features** | | | | |
| Hashtag | The number of hashtags in a tweet | 65.4% | 1.09 | 0.95 |
| $\text{Hashtag}^2$ | Square of the number of hashtags | n/a | 2.09 | 3.44 |
| $\text{Hashtag}^3$ | Cube of the number of hashtags | n/a | 5.16 | 18.05 |
| InitialMention | Mention at the start of a tweet (=1, 0 otherwise) | 2.9% | 0.03 | 0.17 |
| Mention | Presence of a non-initial mention in a tweet (=1, 0 otherwise) | 33.9% | 0.47 | 0.77 |
| URLlink | Presence of a URL link in a tweet (=1, 0 otherwise) | 50.0% | 0.48 | 0.50 |
| **Textual tweet features** | | | | |
| RetweetRequest | Presence of retweet request in a tweet (=1, 0 otherwise) | 0.6% | 0.01 | 0.08 |
| Please | Presence of the word 'please' in a tweet (=1, 0 otherwise) | 0.2% | 0.01 | 0.04 |
| **Visual tweet features** | | | | |
| Photo | The number of photos in a tweet | 57.9% | 0.62 | 0.61 |
| $\text{Photo}^2$ | Square of the number of photos | n/a | 0.75 | 1.52 |
| Video | Presence of video in a tweet (=1, 0 otherwise) | 3.8% | 0.04 | 0.19 |
| **Control features** | | | | |
| LnFollowers | Natural logarithm of number of followers for each brand (to account for non-normality due to a heavy tail distribution) | n/a | 12.74 | 1.33 |
| PromotedTweet | Tweet that has been posted via Twitter Ads platform (i.e. has been paid for) (=1, 0 otherwise) | 1.7% | 0.017 | 0.13 |
| TweetsPerDay | The average number of tweets posted by each brand per day | n/a | 4.13 | 3.18 |
| $\text{TweetsPerDay}^2$ | Square of the number of tweets posted per day | n/a | 27.21 | 38.18 |
| Cashtag | Presence of a cashtag in a tweet (=1, 0 otherwise) | 0.6% | 0.01 | 0.08 |
| **Consumer involvement with product category** | | | | |
| DAuto | Automotive industry (=1, 0 otherwise) | 48% | n/a | n/a |
| DLuxury | Luxury industry (=1, 0 otherwise) | 26% | n/a | n/a |
| DFMCG | FMCG industry (=1, 0 otherwise) | 26% | n/a | n/a |

regression, which allows for over-dispersion of the dependent variable (Cameron & Trivedi, 1986). There were 259 (1.89%) tweets with zero retweets, but the *p*-value for the Vuong test (Vuong, 1989) was 1.00, which implies that the negative binomial model is not adversely affected by excessive zeros in the dependent variable.

The model tested was as follows:

$$\begin{aligned}\text{RetweetCount}_i = {} & \beta_0 + \beta_1\text{Hashtag}_i + \beta_2\text{Hashtag}_i^2 + \beta_3\text{Hashtag}_i^3 + \beta_4\text{InitialMention}_i \\ & + \beta_5\text{Mention}_i + \beta_6\text{URLlink}_i + \beta_7\text{RetweetRequest}_i + \beta_8\text{Please}_i \\ & + \beta_9\text{Photo}_i + \beta_{10}\text{Photo}_i^2 + \beta_{11}\text{Video}_i + \beta_{12}\text{LnFollowers} \\ & + \beta_{13}\text{PromotedTweet}_i + \beta_{14}\text{TweetsPerDay}_i + \beta_{15}\text{TweetsPerDay}_i^2 \\ & + \beta_{16}\text{Cashtag}_i + \beta_{17}\text{DAuto}_i + \beta_{18}\text{DLuxury}_i + e_i\end{aligned} \tag{1}$$

The model shown in Equation (1) was first used for the full sample, and then applied separately to each of the three industries (i.e. Auto, FMCG and Luxury), as discussed in the following section. An alternative model, replacing FMCG with Auto as the reference industry, was also tested to allow estimation of any difference between the two high-involvement industries. The analysis was performed with Stata software, version 14.

## Results

Table 3 shows the estimated coefficients and corresponding *z*-statistics for different specifications of Equation (1) above. That is, Equation (1) was initially run without the non-linear terms (see Model 1 column), and then a square term (Model 2) and cubic term (Model 3) for Hashtag were progressively added. Estimated coefficients and *z* scores for each model are shown in the respective columns, along with their sign and significance. Model 3 revealed significant coefficients for all square terms ($\text{Hashtag}^2$, $\text{Photo}^2$ and $\text{TweetsPerDay}^2$) and $\text{Hashtag}^3$ and a higher Pseudo $R^2$, so the following discussion focuses on Model 3. The marginal effects of the coefficients for that model are shown in the last column, indicating the amount of change in retweet count that is predicted from a one-unit change in the independent variable, after allowing for other factors.

The results for Model 3 show that after allowing for the control variables, InitialMention (an interactive tweet feature) and RetweetRequest (a textual tweet feature) both have a significant positive effect on RetweetCount. In contrast, Mention and URLlink (both interactive tweet features) each have a significant negative linear effect on RetweetCount. In Model 1, where non-linear terms were not included, Video (a visual tweet feature) had a significant negative effect on RetweetCount. However, in both of the models including non-linear terms, Video was not significant. Including the word 'Please' had no significant effect on frequency of retweeting in any of the three models.

Interpreting the results for the three variables where a non-linear relationship was assessed (i.e. Hashtag, Photo and TweetsPerDay), is less straightforward. For these variables, the nature of their relationship with the dependent variable is shown by the sign of the coefficients of the linear and square terms, and for Hashtag, the cubic term, as seen in the results for Model 3. For example, the estimated coefficient for Hashtag is negative, for $\text{Hashtag}^2$ positive and for $\text{Hashtag}^3$ negative, with each significant at the $p < 0.001$ level, implying that inclusion of a minimal number of hashtags in a tweet, *or* including too many hashtags, decreases the number of retweets after allowing for other factors. As a result, the estimated maximum and minimum threshold levels of Hashtag were determined using a process previously used with continuous variables (Mallik, Basu, Hicks, & Sappey, 2014) by differentiating Equation (1) with respect to Hashtag as follows:

Differentiating equation (1) with respect to Hashtag and equating with zero, we get,

$$\frac{d\text{RetweetCount}_i}{d\text{Hashtag}_i} = \beta_1 + 2\beta_2\text{Hashtag}_i + 3\beta_3\text{Hashtag}_i^2 = 0 \tag{2}$$

$$\text{Solving equation (2) for Hashtag, we get Hashtag} = \frac{-2\beta_2 \pm \sqrt{(2\beta_2)^2 - 4 \times 3\beta_3 \times \beta_1}}{2 \times 3\beta_3}$$

The negative coefficient for Hashtag in Model 3 in Table 3, coupled with the minimum level for Hashtag of 1, therefore shows that including one hashtag in a tweet, on average, decreases the retweet count for that tweet compared to a tweet with no hashtag (by a predicted 16.177 retweets; see Marginal Effects, Model 3 above). However, the positive coefficient for $\text{Hashtag}^2$ and the negative coefficient for $\text{Hashtag}^3$, coupled with the estimated maximum for Hashtag of 6, show that the model predicts that including two or more hashtags, up to a maximum of six hashtags, increases the predicted number of retweets of a tweet. A similar process

**Table 3.** Negative binomial model predicting RetweetCount (full sample).

| Model | | Model 1 | Model 2 | Model 3 | Marginal effects Model 3[a] |
|---|---|---|---|---|---|
| | | Estimated coefficients and z scores | | | |
| Interactive tweet features | Hashtag | 0.100*** | −0.025*** | −0.222*** | −16.177*** |
| | | (10.83) | (−1.05) | (−7.63) | (−7.51) |
| | $Hashtag^2$ | | 0.055*** | 0.175*** | 12.710*** |
| | | | (7.15) | (13.09) | (12.53) |
| | $Hashtag^3$ | | | −0.016*** | −1.149*** |
| | | | | (−12.81) | (−12.31) |
| | InitialMention | 0.345*** | 0.391*** | 0.354*** | 25.770*** |
| | | (6.58) | (7.57) | (6.89) | (6.83) |
| | Mention | −0.129*** | −0.115*** | −0.109*** | −7.961*** |
| | | (−10.89) | (−9.86) | (−9.44) | (−9.34) |
| | URLlink | −0.204*** | −0.11*** | −0.122*** | −8.844*** |
| | | (−10.85) | (−6.12) | (−6.54) | (−6.5) |
| Textual tweet features | RetweetRequest | 1.171*** | 1.283*** | 1.270*** | 92.348*** |
| | | (10.52) | (11.79) | (11.71) | (11.53) |
| | Please | 0.261 | 0.150 | 0.139 | 10.109 |
| | | (1.37) | (0.81) | (0.75) | (0.75) |
| Visual tweet features | Photo | 0.801*** | 1.206*** | 1.213*** | 88.206*** |
| | | (40.6) | (42.61) | (43.1) | (35.47) |
| | $Photo^2$ | | −0.227*** | −0.229*** | −16.625*** |
| | | | (−22.79) | (−23.07) | (−21.73) |
| | Video | −0.094* | 0.075 | 0.084 | 6.121 |
| | | (−1.98) | (1.61) | (1.81) | (1.81) |
| Control features | LnFollowers | 0.515*** | 0.605*** | 0.607*** | 44.169*** |
| | | (42.33) | (46.41) | (46.72) | (36.62) |
| | PromotedTweet | 0.892*** | 0.840*** | 0.849*** | 61.767*** |
| | | (13.46) | (12.89) | (13.08) | (12.59) |
| | TweetsPerDay | −0.024*** | −0.290*** | −0.294*** | −21.363*** |
| | | (−7.39) | (−17.03) | (−17.32) | (−16.81) |
| | $TweetsPerDay^2$ | | 0.024*** | 0.025*** | 1.794*** |
| | | | (15.93) | (16.18) | (15.79) |
| | Cashtag | −1.104*** | −0.975*** | −0.956*** | −69.545*** |
| | | (−9.54) | (−8.56) | (−8.43) | (−8.39) |
| Industry | DFMCG | Default reference industry | | | |
| | DAuto | 0.291*** | 0.105*** | 0.084** | 6.098** |
| | | (8.95) | (3.20) | (2.57) | (2.59) |
| | DLuxury | 0.730*** | 0.166*** | 0.139*** | 10.107*** |
| | | (16.29) | (3.16) | (2.65) | (2.66) |
| | Constant | −3.509*** | −4.132*** | −4.096*** | |
| | | (−25.84) | (−29.79) | (−29.61) | |
| | Sample size | 13,712 | 13,712 | 13,712 | 13,712 |
| | Max for Hashtag | N/A | N/A | 6 | |
| | Min for Hashtag | N/A | N/A | 1 | |
| | Max for Photo | N/A | N/A | 3 | |
| | Min for TweetsPerDay | N/A | N/A | 6 | |
| | LR $\chi^2$ ($p$-value) | 11,183.55 | 11,891.52 | 12,003.48 | |
| | | (<0.001) | (<0.001) | (<0.001) | |
| | Pseudo $R^2$ | 0.0788 | 0.0838 | 0.0846 | |
| | Alpha ($p$-value) | 0.9532 | 0.9104 | 0.9039 | |
| | | (<0.001) | (<0.001) | (<0.001) | |

[a]Delta method was used to calculate marginal effects
*, **, *** show significance at $p < 0.05$, <0.01 and <0.001 respectively

was used to obtain maximum and minimum levels for Photo and TweetsPerDay, with the results shown in Table 3.

Table 3 also shows significant differences in RetweetCount depending on the industry, with both Auto and Luxury tweets being retweeted significantly more than the reference industry, FMCG. Analysis of the alternative model (using Auto as the reference industry) showed no significant difference in the frequency of retweeting between the Auto and Luxury industry tweets (data not shown). Comparison of tweet features across the three industries also showed large differences in the usage of different tweet features (see Table 4). For example, 79% of Auto tweets included one or more hashtags, but only 32% of Luxury tweets included a hashtag. Auto tweets were also much more likely to include one or more photos (in 70% of tweets), compared to 35% of FMCG tweets. In contrast, Auto tweets were less likely to include URL links (in 42% of tweets), compared to Luxury, with links in 59% of tweets.

Given the significant difference in retweet rate between industries, as shown in Table 3, and the differences in tweet composition across industries, as shown in Table 4, separate models were run for each industry to test whether the effects of tweet features were consistent across the three industries. The results are shown in Table 5, with estimated coefficients and marginal effects for each industry.

A comparison of the significance and direction of the coefficients across Table 3 (the full sample model) and Table 5 (separate industry models) shows that while the effect of some tweet features is consistent across industries (i.e. RetweetRequest, LnFollowers, Photo and TweetsPerDay), the effect of other variables varies across the three industries. For example, in the full model (Model 3 in Table 3), InitialMention had a significant and positive effect on RetweetCount, and the same effect was observed for the Auto model (see Table 5). However, InitialMention had a significant and *negative* effect on RetweetCount in the Luxury model, and was not significant in the FMCG model (Table 5). Two other variables that were not significant in the full sample model (Video and Please) each had a significant and positive effect

**Table 4.** Percentage and number of tweets with and without tweet features (without outliers).

| | Auto (*n* = 6599) | | FMCG (*n* = 3603) | | Luxury (*n* = 3510) | |
|---|---|---|---|---|---|---|
| | With % (*n*) | Without % (*n*) | With % (*n*) | Without % (*n*) | With % (*n*) | Without% (*n*) |
| Hashtag (1 or more) | 79% (5232) | 21% (1367) | 72% (2593) | 28% (1010) | 32% (1138) | 68% (2372) |
| Hashtag (2 or more) | 36% (2358) | 64% (4241) | 23% (820) | 77% (2783) | 17% (604) | 83% (2906) |
| InitialMention | 3% (209) | 97% (6390) | 2% (75) | 98% (3528) | 3% (112) | 97% (3398) |
| Mention | 40% (2642) | 60% (3957) | 30% (1072) | 70% (2531) | 27% (933) | 73% (2577) |
| URLlink | 42% (2777) | 58% (3822) | 55% (1986) | 45% (1617) | 59% (2096) | 41% (1414) |
| RetweetRequest | 0.4% (27) | 99.6% (6572) | 1.3% (46) | 98.7% (3557) | 0.3% (8) | 99.7% (3502) |
| Please | 0.3% (15) | 99.7% (6584) | 0.2% (4) | 99.8% (3599) | 0.3% (8) | 99.7% (3502) |
| Photo | 70% (4652) | 30% (1947) | 35% (1268) | 65% (2335) | 58% (2027) | 42% (1483) |
| Photo (2 or more) | 3% (194) | 97% (6405) | 0.6% (23) | 99.4% (3580) | 2% (56) | 98% (3454) |
| Video | 5% (363) | 95% (6236) | 1.5% (55) | 98.5% (3548) | 3% (115) | 97% (3395) |
| PromotedTweet | 1% (74) | 99% (6525) | 0.5% (18) | 95.5% (3585) | 4% (141) | 96% (3369) |
| Cashtag | 0.2% (11) | 99.8% (6587) | 2.1% (76) | 97.8% (3527) | 0% (0) | 100% (3510) |

**Table 5.** Negative binomial model predicting RetweetCount for different industries.

| | | Auto | | FMCG | | Luxury | |
|---|---|---|---|---|---|---|---|
| | (2) | Estimated coefficients (z score) (3) | Marginal effects (4) | Estimated coefficients (z score) (5) | Marginal effects (6) | Estimated coefficients (z score) (7) | Marginal effects (8) |
| Interactive features | Hashtag | −0.126** | −7.963*** | −0.102 | −1.185 | −0.326*** | −57.845*** |
| | | (−3.06) | (−3.05) | (−1.32) | (−1.32) | (−5.65) | (−5.6) |
| | Hashtag$^2$ | 0.124*** | 7.824*** | 0.140 ** | 1.625** | 0.123*** | 21.739*** |
| | | (6.99) | (6.83) | (2.44) | (2.44) | (3.28) | (3.27) |
| | Hashtag$^3$ | −0.011*** | −0.701*** | −0.020 | −0.231 | −0.013** | −2.388** |
| | | (−7.00) | (−6.84) | (−1.73) | (−1.73) | (−2.33) | (−2.33) |
| | InitialMention | 0.552*** | 34.826*** | 0.151 | 1.747 | −0.464*** | −82.189*** |
| | | (7.73) | (7.59) | (1.33) | (1.33) | (−5.15) | (−5.06) |
| | Mention | −0.119*** | −7.476*** | −0.047* | −0.549* | 0.028 | 4.961 |
| | | (−7.48) | (−7.37) | (−2.05) | (−2.05) | (1.01) | (1.01) |
| | URLlink | 0.023 | 1.474 | −0.119*** | −1.382*** | −0.320*** | −56.634*** |
| | | (0.82) | (0.82) | (−3.47) | (−3.45) | (−8.29) | (−7.98) |
| Textual features | RetweetRequest | 0.884*** | 55.717*** | 1.505*** | 17.452*** | 1.626*** | 288.108*** |
| | | (4.8) | (4.77) | (10.89) | (10.12) | (5.3) | (5.23) |
| | Please | 0.489* | 30.851* | −0.615 | −7.127 | −0.632 | −111.963 |
| | | (1.99) | (1.99) | (−1.17) | (−1.17) | (−1.85) | (−1.85) |
| Visual features | Photo | 1.100*** | 69.351*** | 0.872*** | 10.108*** | 1.783*** | 315.839*** |
| | | (24.78) | (24.75) | (17.20) | (17.20) | (23.62) | (23.62) |
| | Photo$^2$ | −0.192*** | −12.081*** | −0.194*** | −2.255*** | −0.378*** | −66.955*** |
| | | (−13.73) | (−13.73) | (−8.13) | (−7.91) | (−20.11) | (−17.26) |
| | Video | −0.103 | −6.523 | 0.151 | 1.745 | 0.522*** | 92.508*** |
| | | (−1.72) | (−1.72) | (1.15) | (1.15) | (5.58) | (5.53) |
| Control features | LnFollowers | 0.561*** | 35.386*** | 1.053*** | 12.206*** | 0.967*** | 171.394*** |
| | | (26.25) | (22.37) | (28.72) | (22.21) | (34.51) | (21.96) |
| | PromotedTweet | −0.054 | −3.377 | 0.444* | 5.153* | 1.127*** | 199.613*** |
| | | (−0.47) | (−0.47) | (2.03) | (2.03) | (14.33) | (12.45) |
| | TweetsPerDay | −1.255*** | −79.102*** | −1.142*** | −13.238*** | −1.042*** | −184.597*** |
| | | (−14.72) | (−14.72) | (−17.54) | (−15.3) | (−20.02) | (−16.16) |
| | TweetsPerDay$^2$ | 0.215*** | 13.542*** | 0.115*** | 1.337*** | 0.084*** | 14.855*** |
| | | (11.95) | (11.49) | (17.67) | (15.39) | (19.62) | (15.97) |
| | Cashtag | −0.316 | −19.890 | −0.846*** | −9.807*** | N/A | N/A |
| | | (−1.32) | (−1.32) | (−6.01) | (−6.01) | | |
| | Constant | −2.323*** | | −7.902*** | | −7.866*** | |
| | | (−8.48) | | (−23.35) | | (−22.75) | |
| | Sample size | 6599 | | 3603 | | 3510 | |
| | Max for Hashtag | 7 | | 4 | | 4 | |
| | Min for Hashtag | 1 | | 1 | | 2 | |
| | Max for Photo | 3 | | 2 | | 2 | |
| | Min for TweetsPerDay | 3 | | 5 | | 6 | |
| | LR $\chi^2$ (p-value) | 2217.83 | | 1493.24 | | 2894.59 | |
| | | (<0.001) | | (<0.001) | | (<0.001) | |
| | Pseudo $R^2$ | 0.0328 | | 0.0595 | | 0.0681 | |
| | Alfa (p-value) | 0.89626 | | 0.78884 | | 0.74039 | |
| | | (<0.001) | | (<0.001) | | (<0.001) | |

*, **, *** show significance at $p < 0.05$, <0.01 and <0.001 respectively

on RetweetCount in one industry (respectively, Luxury and Auto). Other variables (i.e. Mention, URLlink and Cashtag), each negatively and significantly associated with RetweetCount in the full model, were not significantly associated with RetweetCount in one of the three industries. For Hashtags the same direction of non-linear pattern was observed for each industry, though for FMCG the linear and cubic terms were not significant, and the models estimated different minimum and maximum thresholds.

## Discussion

Several insights emerge from the analysis. Previous studies have examined the effect of different tweet features on retweeting, in some cases using non-brand tweets (e.g. Naveed et al., 2011; Petrovic et al., 2011) and in others, examining retweeting of brand tweets (Araujo et al., 2015; Burton, Dadich, & Soboleva, 2013; Kim et al., 2014), as in this study. However, previous multivariate models examining the effect of tweet features have not tested for differences across products representing different levels of consumer involvement, despite strong theoretical arguments to suggest a difference, as discussed in the literature review. This research shows that consistent with theoretical and empirical evidence that consumers' involvement with a product category can influence their response to brand communications, tweets from high-involvement brands were retweeted significantly more often than tweets from low-involvement brands, after allowing for other predictors in the model. However, the effect of some tweet features varied across low- and high-involvement product categories, as we discuss in the following sections. In addition, the results suggest changing consumer responses to tweet features, in particular in consumers' response to interactive tweet features, reflecting the evolving nature of Twitter.

Most notably, the results show that after allowing for the control variables, only two independent variables – one textual (RetweetRequest), and the other visual (Photo) had a consistent effect on retweeting across industries – in both cases positive, though non-linear for Photo. Earlier research has consistently highlighted the positive effect of retweeting requests (e.g. Boyd, Golder, & Lotan, 2010; Malhotra et al., 2012), and these results show that effect is the same across industries representing different levels of consumer involvement. Our finding of a consistent positive effect of photos on retweeting contrasts with previous research that did not find an increase in retweeting for tweets that contained links to photos (Malhotra et al., 2012). However, that research predated the ability to embed photos and/or video in tweets. Our finding that *embedded* photos were associated with a significant increase in retweeting suggests that technical evolution in Twitter (i.e. by allowing photos to display without a consumer clicking on a link) has resulted in increased response to photos. This positive effect of photos on retweeting across industries is in line with earlier advertising research that demonstrated the benefits of images in advertisements (Rossiter & Percy, 1980; Unnava & Burnkrant, 1991). This convergence between the effect of images in advertisements and in tweets may reflect that both communication channels push an image to the consumer, and thus increase the probability of a consumer response.

The effect of Hashtag (an interactive tweet feature) was also largely consistent across industries representing different levels of consumer involvement, with the sole exception being a non-significant effect of the linear term for Hashtag in the FMCG industry, albeit in the same direction. This result is not unexpected, since previous research has repeatedly demonstrated that tweets with hashtags are retweeted more often, on average (e.g. Boyd et al., 2010; Suh et al., 2010). As a result, hashtags are very widely used, appearing in more than 70% of Auto and FMCG tweets (see Table 4). However, to the best of our knowledge, there is no existing research that estimates minimum and maximum thresholds to identify the non-linear relationship between the number of hashtags and predicted retweet count. While the optimal maximum and minimum number of hashtags varied across industries, the results suggest that organisations may benefit from experimenting with different numbers of hashtags, and assessing the results.

The effect of another interactive tweet feature, URLlink, on retweeting was also largely consistent across industries, with inclusion of a URL link associated with a significant negative effect on retweeting in the full model and FMCG and Luxury industries, though a non-significant effect in the Auto industry. In this case, however, the negative direction of effect is particularly interesting, since as discussed in the literature review, earlier studies have repeatedly found that inclusion of a URL link is associated with a higher frequency of retweeting (e.g. Naveed et al., 2011; Son et al., 2013; Suh et al., 2010). The reasons for the observed negative effect of URL links are not clear: some previous studies did not allow for the effect of other factors (e.g. Soboleva et al., 2015; Zarella, 2013), so methodological differences may explain these different findings. It is also possible that the evolution of Twitter, including the recent ability to embed content (such as photos and videos), within the tweet means that recipients of tweets may now be less likely to click on a URL link to reveal hidden content, and thus less likely to forward such tweets.

In contrast with the largely consistent results discussed above, there was notably less consistency across industries for other tweet features and, in particular, significant differences across the two high-involvement industries. Most striking, perhaps, is the effect of mentions. An initial mention had a significant positive effect on retweeting for Auto industry tweets, but a significant negative effect for Luxury tweets, and no significant effect for FMCG tweets. In contrast, a mention elsewhere in the tweet had a significant negative effect on retweeting for both Auto and FMCG industries, and was not significant for Luxury. Earlier studies have generally found that mentions decrease retweeting (Petrovic et al., 2011; Tan et al., 2014). However, previous research has not differentiated between effects of initial mentions and mentions elsewhere in a tweet. These results show that the effect of a mention is very different depending on its location in a tweet, but the effect is not consistent across industries. As discussed in the literature review, initial mentions can attract attention by making the mentioned Twitter handle (e.g. a person, possibly a celebrity, or a brand handle), the subject of the tweet. But within these two categories of person and a (non-person) brand, there is also substantial variation; a mentioned person may be a celebrity, thus potentially increasing attention to the tweet, and consequently increasing the retweet rate, especially if strategic fit is present between that celebrity and a brand's product (Davies & Slater, 2015). (A tweet beginning with a Twitter handle name can also be a reply, including what has been called a 'public reply', but as discussed previously, there were very few public replies in the data (35), and all replies were excluded from analysis since they are less likely to be retweeted.) A tweet commencing with a mention of a brand may refer to the brand itself, such as @Burberry's tweet (below) showing an image of its well-known check emblem, or may refer to an unrelated brand, such as @MercedesBenz' tweet (below) referring to a list of the best cars in the world by Top Gear (a well-known TV show):

> .@Burberry trench coats have evolved over time but their check lining is still a signature feature http://t.co/lnFJytihZx (retweeted 216 times) [originally accessed on 14 September 2014]

> .@BBC_TopGear's "Best Cars In The World"? We've got a Coupé for that: benz.me/ynziDK/ http://t.co/wQAqxnw8e0 (posted by @MercedesBenz, retweeted 189 times) [originally accessed on 5 October 2014].

The effect of mentions is, therefore, more complex than has been reflected in the literature to date. These results suggest that mentions can increase the number of retweets, if the mention is at the start of a tweet, as demonstrated by the significant effect of initial mentions for Auto industry tweets. However, this effect was not consistent across industries, and thus these results suggest that the effect of initial mentions merits further research. Such research could compare the effects of different types of initial mentions, for example, third-party mentions (i.e. celebrities or other brands) and self-mentions by brands.

The results for inclusion of the word 'please' were similarly inconsistent, being significantly positive in the Auto industry, marginally negative for Luxury, and not significant for FMCG. However, these varying results are likely to be due to the low number of occurrences of the word 'please' (a total of only 27), in nearly all cases unassociated with a retweet request (which, as noted above, had a consistent and positive effect on the frequency of retweeting). As discussed in the literature review, there are theoretical reasons to suggest that adding the word 'please' to a retweet request may increase the retweet rate, though the very low use of 'please' by major brands in the context of a retweet request means that detecting any significant effect will require large samples to identify what appears to be, at best, a very small effect.

The final inconsistent (and surprising) result was the effect of inclusion of video (a visual tweet feature) in a tweet, which was associated with a significant increase in the number of retweets for the Luxury industry, but a marginal decrease for the Auto industry (and no significant effect for FMCG). Video sharing has become common in social media (Daggan, 2013), but as mentioned above, the ability to embed video is a relatively recent innovation on Twitter (Cooper, 2013). Reflecting its relative novelty, only one study to date appears to have analysed the effect of embedded video on retweeting, after allowing for other factors. That study found that the presence of video in tweets (of a US based patient/health advocacy coalition) did not result in any significant increase in the retweet rate (Saxton et al., 2015). These results show that the use of video can result in an increase in retweeting, as shown here in the Luxury industry. However, the effect of video was not consistent, as shown by the marginal negative effect in the Auto industry and the absence of a significant effect in the FMCG industry. These inconsistent results for video are remarkable, given the additional richness in content offered by video (de Vries et al., 2012), and earlier evidence that animated banner ads appear to increase click-through intention and advertising recall (Yoo et al., 2004). It is possible that the varying effects of video are, like URL links, explained by the evolution of Twitter. Like URL links, to play a video on Twitter, a user must click on a video to enable sound and watch it for some time, which requires sustained attention (Bruni et al., 2012). (Videos will usually commence autoplay as a user scrolls through their Twitter feed, but sound is not enabled and the video stops playing if the user continues to scroll.) It is also possible that video content with prominent logos may be perceived by followers as a form of advertising and as a result create aversion (Teixeira, 2012), making followers less likely to share brand tweets containing video.

Finally, previous research suggests that videos that entertain and connect with consumers are reshared more often than those with a utilitarian purpose (Yang & Wang, 2015), so Luxury tweets with videos may have been seen as more entertaining, and thus retweeted more often.

So what are the implications of these results for research and for marketing managers? In developing and testing a theoretical model to predict brand eWOM on Twitter, we provide important directions for research and for practice. For researchers, we extend previous research on Twitter, by showing how interactive and other tweet features increase consumer engagement with tweets, as measured by the frequency of retweeting. Consistent with research into the importance of consumer involvement, we show that retweeting is significantly higher in high-involvement product industries, even though those who followed the low-involvement brands in this study are likely to be more involved with the brand and/or product than a typical consumer. Building on previous research into different types of interactivity, we show that tweets (an interactive communication method) can be classified as to whether they contain interactive and/or textual features that can increase (or in some cases, decrease) the frequency of retweeting. We also show that the effect of some tweet features on retweeting is consistent across industries representing different levels of consumer involvement, while for other tweet features, the effect is inconsistent. Therefore, consumer involvement appears to have a significant effect on retweeting, but contrary to expectations, the effect of tweet features varied across industries, and was not consistent across the two high-involvement industries. The reasons are not obvious and merit further research. However, the differences may relate to different uses of social media across and within industries representing different levels of consumer involvement. For example, as shown in Table 4, the two high-involvement industries had very different levels of usage of some tweet features (i.e. Mentions and URLlinks). In addition, the effect of mentions on retweeting will almost certainly vary according to the interest of a brand's followers in the mentioned handle, and classifying mentions by who or what was mentioned, and attempting to determine follower interest in the mentioned handles, was outside the scope of this study. Understanding the reasons for across-industry differences is thus an area for further research, as we discuss below, but our model provides a framework for improved classification of tweet features, which should contribute to more accurate prediction of the retweeting of brands' tweets.

For managers, the results reveal a number of strategies for increasing retweeting of brands' messages. Though we controlled for the reach of tweets in this study, the results show that any strategy that increases the reach of tweets (e.g. increasing follower numbers and/or promoting tweets) is likely to increase the retweet count, and previous research suggests that an interactive, one-to-one and reciprocal approach may assist in establishing a larger follower base (Aleti, Harrigan, Cheong, & Turner, 2016). In contrast with findings that have suggested that only a small number of tweets per day – as few as three – is necessary (Lovejoy et al., 2012) and that more frequent tweeting does not result in a higher number of retweets (Mamic & Almaraz, 2013), these results suggest that a minimum number of tweets per day is required to increase the number of retweets (3, 5 and 6 tweets for Auto, FMCG and Luxury, respectively).

Beyond the strategies to increase reach discussed above, the results show that tweet design can be used by brands to encourage – or 'seed' – retweeting of their tweets. As discussed above, inclusion of hashtags, photos and retweet requests was consistently associated with higher retweet rates across the three industries (albeit in a non-linear fashion for hashtags and photos). In contrast, inclusion of URL links and mentions (other than at the start of a tweet, where results were inconsistent) was associated with *lower* rates of retweeting. For initial mentions and video, the results were inconsistent across industries, so different brands may or may not benefit from including them in their tweets. So, the results show that some tweet design strategies are likely to have a consistent benefit across industries, but that the effect of others is likely to vary across industries, suggesting that companies need to develop and test different approaches to maximise the likelihood of their tweets being retweeted.

### *Directions for further research*

The results suggest several avenues for further research. Firstly, while the overall model showed that tweets sent by high-involvement brands were significantly more likely to be retweeted, there were different predictors of retweeting across the two high-involvement industries, and these predictors were not consistently different from the low-involvement FMCG industry. The reasons underlying this surprising finding are not clear, but further research comparing different product categories would be valuable to examine whether established classification of involvement predicts the behaviour of brand followers on Twitter.

The inconsistent effects of video on retweeting also merit further investigation, given the disparity in results across the three industries. Future research could benefit by examining the different types of video included in tweets, to determine if particular types of video are associated with higher (and lower) rates of retweeting. Similarly, a closer examination of the content of photos in tweets may provide further insights into why brand tweets get retweeted. Finally, as discussed above, further research could investigate the largely unexplored area of initial mentions, and whether third-party mentions and/or self-mentions by brands are most effective in increasing retweet rates.

### *Limitations*

As with all studies, there are limitations to the research. Firstly, the study only analysed Twitter activity by leading brands with large numbers of followers. These brands will all have high consumer awareness and large marketing budgets and teams at their disposal. The results may, therefore, not be applicable to brands with lower consumer awareness and smaller marketing budgets. The second limitation of the study relates to one of the control variables – the use of promoted tweets. While the study is one of the first to examine the effect of promoted tweets, we were only able to identify promoted tweets that were posted through Twitter's own advertising platform (Twitter for Ads). At the time of data collection, the vast majority of promoted tweets were posted through this platform, but it is possible that some tweets were promoted using other content management platforms, so our coding may not have identified all promoted tweets. While any associated underestimation of the count of promoted tweets would decrease the power of the study to identify a significant effect in this area, it should not invalidate other results. Finally, the amount spent on promoting any tweet is not publicly available, so our estimation of the effect of promoted tweets does not allow for different levels of promotion. The study is also limited by what it did not assess: most importantly, due to the large number of tweets examined, we did not incorporate tweet content (such as sentiment) beyond the inclusion of textual and/or the specified interactive features of the tweets. As well as the areas for future research discussed above, future research could extend this analysis by incorporating measures of tweet sentiment (e.g. negative, positive, neutral) and/or other measures of tweet content. The study also could not exclude the possibility that some of the retweets counted were sent by bots, though we have no evidence to suggest that this occurred.

## Disclosure statement

No potential conflict of interest was reported by the authors.

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# Appendices

## Appendix 1. List of brands and Twitter handles examined

| Brand | Twitter handle |
|---|---|
| **Automotive industry** | |
| Audi | @Audi |
| BMW | @BMWUSA |
| Chevrolet | @chevrolet |
| Ferrari | @FerrariUSA |
| Ford | @Ford |
| Harley Davidson | @harleydavidson |
| Honda | @Honda |
| Hyundai | @Hyundai |
| Kia | @Kia |
| Mercedes Benz | @MercedesBenz |
| Nissan | @NissanUSA |
| Porsche | @Porsche |
| Toyota | @Toyota |
| Volkswagen | @VW |
| **FMCG** | |
| Avon | @AvonInsider |
| Colgate | @Colgate |
| Danone | @Danone |
| Duracell | @Duracell |
| Gillette | @Gillette |
| Johnson & Johnson | @JNJNews |
| Kellogg | @KelloggCompany |
| Kleenex | @Kleenex |
| L'Oreal | @LOrealUSA |
| Nestle | @Nestle |
| Pampers | @Pampers |
| **Luxury** | |
| Burberry | @Burberry |
| Cartier | @Cartier |
| Gucci | @gucci |
| LouisVuitton | @LouisVuitton |
| Prada | @Prada |
| Ralph Lauren | @RalphLauren |
| Tiffany and Co | @TiffanyAndCo |

## Appendix 2. Correlations and significance

| | Retweet Count | Hashtag | URL link | Initial Mention | Mention | Retweet Request | Please | Cashtag | Photo | Video | Ln Followers | Promoted Tweet | Tweets Per Day |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Retweet Count | 1 | | | | | | | | | | | | |
| Hashtag | 0.0188 | 1 | | | | | | | | | | | |
| | 0.0281 | | | | | | | | | | | | |
| URLlink | −0.0805 | −0.1183 | 1 | | | | | | | | | | |
| | <0.001 | <0.001 | | | | | | | | | | | |
| Initial Mention | 0.0044 | −0.0293 | −0.0451 | 1 | | | | | | | | | |
| | 0.6039 | 0.0006 | <0.001 | | | | | | | | | | |
| Mention | −0.0104 | −0.0065 | −0.1527 | 0.238 | 1 | | | | | | | | |
| | 0.2237 | 0.4452 | <0.001 | <0.001 | | | | | | | | | |
| Retweet Request | 0.0039 | −0.0226 | −0.0449 | −0.0133 | −0.0424 | 1 | | | | | | | |
| | 0.644 | 0.0082 | <0.001 | 0.1196 | <0.001 | | | | | | | | |
| Please | 0.0051 | −0.0026 | −0.0193 | −0.0077 | 0.0005 | −0.0034 | 1 | | | | | | |
| | 0.5525 | 0.7585 | 0.0238 | 0.3698 | 0.9492 | 0.6885 | | | | | | | |
| Cashtag | −0.0256 | −0.0012 | −0.0151 | −0.0138 | −0.0316 | −0.0062 | −0.0036 | 1 | | | | | |
| | 0.0027 | 0.886 | 0.0763 | 0.1065 | 0.0002 | 0.4706 | 0.6776 | | | | | | |
| Photo | 0.1877 | 0.0701 | −0.2281 | 0.0171 | 0.0454 | −0.0426 | 0.0089 | −0.0743 | 1 | | | | |
| | <0.001 | <0.001 | <0.001 | 0.0457 | <0.001 | <0.001 | 0.2975 | <0.001 | | | | | |
| Video | −0.03 | 0.0303 | −0.1675 | −0.0122 | 0.012 | −0.0155 | −0.0089 | −0.0161 | −0.1887 | 1 | | | |
| | 0.0004 | 0.0004 | <0.001 | 0.1548 | 0.161 | 0.0695 | 0.2956 | 0.0598 | <0.001 | | | | |
| LnFollowers | 0.2646 | −0.0123 | −0.0674 | 0.0341 | 0.0942 | −0.0319 | 0.005 | −0.1084 | 0.1676 | 0.0882 | 1 | | |
| | <0.001 | 0.1483 | <0.001 | 0.0001 | <0.001 | 0.0002 | 0.5597 | <0.001 | <0.001 | <0.001 | | | |
| Promoted Tweet | 0.0855 | −0.045 | 0.0213 | −0.0092 | −0.0543 | −0.0101 | −0.0058 | −0.0105 | 0.0007 | −0.0177 | 0.0505 | 1 | |
| | <0.001 | <0.001 | 0.0126 | 0.2816 | <0.001 | 0.2353 | 0.4941 | 0.2185 | 0.9392 | 0.0384 | <0.001 | | |
| Tweets Per Day | 0.0167 | −0.2559 | 0.168 | −0.0443 | −0.1917 | −0.0039 | −0.0137 | −0.0463 | −0.2245 | −0.0846 | 0.2096 | 0.0242 | 1 |
| | 0.0509 | <0.001 | <0.001 | <0.001 | <0.001 | 0.6513 | 0.108 | <0.001 | <0.001 | <0.001 | <0.001 | 0.0046 | |