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What Attracts Followers?
Exploring Factors Contributing to Brand Twitter Follower Counts

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ABSTRACT

Although business and researchers acknowledge the importance of social media, little research has been conducted to explore what attracts people to follow brand Twitter accounts. This research attempts to achieve an analytical understanding of the factors that contribute to brand Twitter follower count based on social network and communication theories. Using data from 346 Twitter accounts spanning 48 industries and 31 countries, the authors found that the quality and quantity of tweets, as well as social learning of brand Twitter accounts are positively related to brand Twitter account followers; contrary to popular belief, the use of hashtags and links and interactivity with users are not positively related to brand Twitter account followers. The study is among the first to investigate what attracts brand Twitter account followers, which offers important strategic recommendations for brand social media managers on how to manage their social media accounts.

KEYWORDS

Brand Twitter Accounts, Social Learning, Social Media, Twitter Followers

INTRODUCTION

The era of social media has afforded new communication channels for businesses in attracting, developing, and maintaining customers (Li, Berens, & Maertelaere, 2013; Wamba, Akter, Bhattacharyya & Aditya; 2016). Social media, i.e., the Internet-based applications that allow the creation and exchange of user-generated content (Kaplan & Haenlein, 2010) has gained strategic importance as a powerful new form of electronic word of mouth, reported being approximately twenty times more effective than marketing events and thirty times more effective than media appearances (Trusov, Bucklin & Pauwels, 2009). Research found that followers of brand on social media have higher trust and brand identification (Kim, Sung, & Kang, 2014; Maldonado & Sierra; 2016; Díaz-Díaz & Pérez-González; 2016), are more loyal to the brand (Laroche, Habibi, Richard & Sankaranarayanan, 2012; Laroche, Habibi & Richard, 2013), have higher customer purchase intentions (Goh, Heng & Lin, 2014; Kim & Ko, 2012), buy more frequently, and are more profitable (Rishika, Kumar, Janakiraman & Bezawada, 2013). Social media engagements also enhance brand equity, relationship equity, and value equity

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(Kim & Ko, 2012; Yu, Duan & Cao, 2013). Twitter, a microblogging and social networking service, in particular, is noteworthy. Launched in 2007, Twitter now has 330 million monthly active users, 500 million tweets per day, and 80% users on mobile (as of September 2019). Twitter has become the social platform of choice for brands' customer engagement, with 413 companies (83%) of the Fortune 500 active on Twitter (Barnes & Andonian, 2014).

Although business and researchers acknowledge the strategic importance of social media, little research has been conducted to explore what attracts people to follow brands' twitter accounts. Follower count is a key metric for social media marketing as it is Twitter's most basic currency (Hutto, Yardi, & Gilbert; 2013). The followers form an audience to the brand and provide the brand access to a network of social ties, resources, and influence (Hutto et al., 2013). Most prior research has addressed brands' Twitter followers from either the brand relationship or the need satisfaction perspective. Research reported that users follow a brand on Twitter to engage in the brand community (Phua, Jin & Kim; 2017), or as a result of brand attachment (Chu, Chen, & Sung; 2016). Yang (2011) argued that by following a brand's Twitter account, individuals fulfill the sense of belonging and citizenship. Zhu & Chen (2015) thought that individuals seek self-esteem and relatedness by following brands on Twitter. However, these researches are from a follower's perspective, i.e., what followers need and want. Most of them have used psychological measures as the dependent variable, rather than actual follower counts. Furthermore, little research has explored the features of brand activities (e.g., interaction, frequency of posting) and their impact on follower counts.

A few scholarly works have revealed some preliminary findings regarding follower count from the account activity perspective. Hutto et al. (2013) reported that message content, social behavior, and network structure could predict follower counts for Twitter accounts. Unfortunately, the research was only geared toward individual Twitter accounts, not business or brand accounts, with no brand-related variables in the model. Levine, Mann & Mannor (2015) found that learning actively online can provide deeper insights into how to attract followers. Stevanovich (2012) argued that engaging users, developing relationships and compelling content are key components of success in social media discourse. Mueller & Stumme (2017) explored how user profiles on Twitter affect follower counts. Despite these pioneer works, no comprehensive research that integrates both the communication perspective and social network perspective has been conducted specifically on business Twitter accounts. This paper attempts to achieve an analytical understanding of the factors that contribute to the number of followers for brands on Twitter based on an integrative model encompassing both the communication perspective and social network perspective with a comprehensive set of variables selected based on sound theoretical framework. Specifically, we seek to examine how Grice's Maxims of communication, social learning and social interactivity contribute to brands' twitter follower counts and present strategic recommendations for social media marketing managers. Our results highlight the importance of quality of the tweets, tweet presentation, tweet frequency and social learning to follower counts.

This research contributes to the literature in two ways. First, for practitioners, the number of followers has long been used as a main performance index for social media metrics (Adweek, 2011). However, most of the results are from trade journals or bloggers, while academic research that is based on theory and empirically tested is little. Thus, this research helps to clarify the question of how to attract Twitter followers for brands managing their Twitter accounts, and gives a clear picture to brand social media managers about what to do based on a theory-guided, and empirically validated research. Second, theoretically, this research contributes by integrating research from both the communication perspective and the social network perspective to develop and test a theoretically and empirically driven model of contributing to brands' Twitter follower counts. By grounding our model in theories of communication and social networks, we highlight the significant role of quality and quantity of Tweets, the presentation of Tweets from the communications perspective, and social learning from the social networks perspective as key drivers of Twitter follower counts.

In the following sections, we will first give an overview of brands' Twitter accounts and an explanation of the ways in which brands' Twitter accounts operate. We will next describe the nature of the Twitter data we use for our exploratory analyses, offer basic descriptive results, and develop our hypotheses. Then, the paper will provide a few in-depth analyses of the variables linked to brand twitter follower counts.

BRAND TWITTER ACCOUNT ACTIVITIES

Twitter allows corporations to build brand pages with customizable logos and features. Brands are able to build a profile that consists of their user name, photo, bio, as well as their website on Twitter, which people, as well as other brands, can follow to see all the postings by the brand. Brands post Tweets, short messages that are up to 280-characters in length, which are visible to all users and updated in their followers' timelines. Users can choose to retweet original messages from other accounts. Retweets enable users to spread information of their choice beyond the reach of the original tweet account's followers. Users can also express their love for a certain Tweet by marking it as a "Favorite", which is a small star icon at the bottom of the Tweet. Twitter designed the Favorite mechanism to allow users a virtual way of saying them like it enough to mark it.

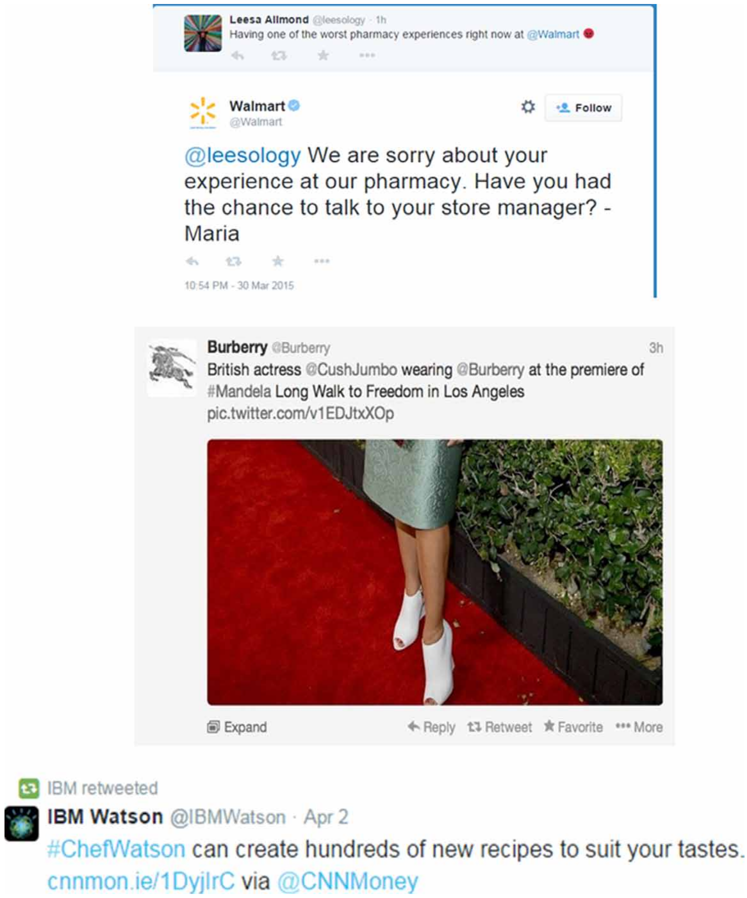
Twitter offers some tools to organize users' posting. For example, you can add categories to your tweet by using "hashtag", i.e., the # symbol (e.g. #BlackFriday) either as they appear in a sentence, e.g., "Find the Best #BlackFriday Deals" or appended to it like "Find the Best Black Friday Deals. #BlackFriday". A hashtag allows grouping of similarly tagged messages, as well as allowing a keyword search to return all messages that contain it. The hashtag function has been implemented across different social platforms besides Twitter, such as Facebook, Pinterest, and Instagram, to allow for easy searching and content-categorization. You can also mention other users in tweets to direct it towards them by using the @ symbol (e.g. @twitter). The users that are mentioned in the tweets will be able to see the message at their timeline and respond to it. Figure 1(a) below shows how we can use the @ symbol to direct the conversation.

Although Twitter has a 280 characters limit, you can embed links to your tweets to direct users to more details. If the link points to a picture, the picture will automatically be displayed in non-mobile browsers. Figure 1b below shows on embedded links look like in tweets. As tweets are a blend of messages and symbols such as # and links to other resources, the presentations of tweets can vary from easily readable to needing efforts to decipher. For example, This Tweet from IBM, "RT @ IBMWatson: #ChefWatson can create hundreds of new recipes to suit your tastes.cnnmon.ie/ 1DyjIrC via@CNNMoney http://t.co/JLB Pcyc..." takes more processing to understand than plain English does. Figure 1c shows an example of complex tweets with hashtags and links.

THEORETICAL BACKGROUND AND HYPOTHESES

Although no prior research has directly addressed factors contributing to brands' Twitter followers count, there have been some related pioneer work in this field. Hutto et al. (2013) selected a total of 22 variables based on various theories and reported that for individual accounts on Twitter, informational content, the burstiness of tweeting, and profile elements (i.e., length of description, URL, and location) emerged as significant positive predictors of follower growth. Broadcast content (e.g., content not addressed to a specific recipient) and negative sentiments in Tweets are negatively related to follower growth. The number of followers and network overlap also contributes to follower growth. Levin et al. (2015) designed a mechanism for online agents to manage Twitter accounts via learning from its own history. Their result found that learning actively is an effective way to attract followers. Stevanovich (2012) emphasized the similarities of Twitter and other communication media and approached Twitter from a communication theory perspective. Through rhetorical analysis, the research showed that brands can achieve success in social media by engaging users, developing

Figure 1.



relationships and providing compelling content (Stevanovich, 2012). Mueller & Stumme (2017) proposed a classifier that labels users who will increase their followers based on different types of profile names and profile features such as whether there is a description or URL.

Twitter, as a new form of computer-mediated media, combines both social interaction/social networks and news media (Fischer & Reuber, 2011; Kwak, Chun & Moon; 2011). Indeed, as Stevanovich (2012) observed, social media is like other communication vehicle that demands the use of sound rhetoric and communication theories and applications. Twitter is used as a source of information (Westerman, Spence & van der Heide; 2012) as well as a social network platform (Lee & Kim, 2014). Thus, it is helpful to examine Twitter from both the communication perspective and the social network perspective.

Reeves & Nass (1996) observed that people tend to treat computers and new media as if they were either real people and respond to them naturally and socially, as they would either to another person, such as by being polite, cooperative, attributing personality characteristics such as aggressiveness, humor, expertise, and even gender. This observation broadens the application of some communication theories to the realm of human-computer interaction, of which Grice's Maxims (Grice, 1975) is one. Grice argued that people generally feel that conversations should be guided by four basic principles: quality, quantity, relevance, and manner (Grice, 1975). First, the maxim of quantity requires that the communicator to be as informative as one possibly can, and gives as much information as is needed, and no more. Second, the maxim of quality asks for truthful and evidence-based content. Third, the maxim of relevance seeks relevant and pertinent content. Finally, the maxim of manner demands clear, brief, and orderly communication without obscurity and ambiguity.

Grice's Maxims (Grice, 1975) have been widely used not only in face-to-face communication but also in computer-mediated communications (Baratgin, Jacquet & Cergy.;2019; Berendt, Günther & Spiekermann; 2005; Herring, 1999). Herring (1999) applied the Maxim of relevance and examined online interaction coherence. Baratgin et al. (2019) applied Grice's Maxims in chatbot and found that these maxims had a particularly important impact on response times and the perceived humanness of a conversation partner. Berendt et al. (2005) found Grice's Maxims as a popular guideline in on-line agent communication design.

Based on Grice's Maxims (Grice, 1975) and the unique features of social networks, this research proposes a research framework that encompasses both the communication perspective and the social network perspective to account for the factors contributing to brand Twitter accounts' follower numbers. The research framework is depicted in Figure 2 below.

The Communication Perspective

For the communication perspective, this research adopts Grice's Maxims as a guiding theory, which provides four principles to achieve effective communication. As the Maxims were designed for human conversation, when applying it to the Twitter context, some adaptions are necessary. We modified some of the content of the maxims below for our research:

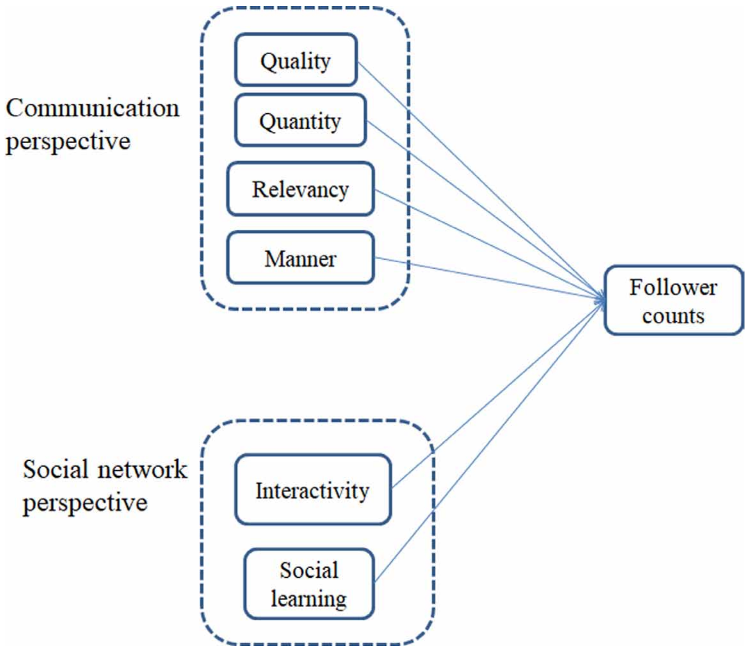
1. **Maxims of Quality:** Tweet content should be true and of good quality. This can be gauged by the percentage of content that is favorited by users.
2. **Maxims of Quantity:** The numbers of Tweets should suffice to convey enough information for the brand. The quantity of communication can be measured by the frequency of tweeting by brands.
3. **Maxim of Relevance:** Tweet content should be relevant. On Twitter, relevance is defined as the match between the follower's information needs and the information corporation accounts provide. As Nielson's (2013) Twitter Consumer Survey showed, most people following brand want to get information concerning the brand itself: promotions, offers, brand news, etc. It seems that the relevance of the brand's twitter account is about the brand itself: original messages from, and about the brand. The relevance of content can be measured by the percentage of original content in Tweets.
4. **Maxims of Manner:** Tweets should have a clear, easy-to-understand presentation. The manner on Twitter can be measured by the percentage of tweets with a clean and neat presentation, without the use of complex symbols and links.

Quality

The first maxim is about the quality of the messages. Gallup's research reported that to follow trends and find information is one of the main reasons for people to use social media (Gallup, 2014). Users actively engage in social media to fulfill their informational needs (Phua et al., 2017). Hutto et al. (2013) found that the percentage of informational content is a top predictor of individual Twitter follower counts. As users go on twitter to find information, the quality of the messages (informative vs. un-informative) from brand Twitter accounts will be positively associated with follower counts. Users typically will unfollow an account due to low-quality content (Kwak et al., 2011). Accounts offer high-quality content that is informative, on the contrary, will attract more users than accounts that do not. Therefore,

H1: The quality of messages from brands' Twitter accounts is positively related to brand Twitter follower counts.

Figure 2. Research framework



Quantity

The maxim of quantity states that you should provide enough messages to explain yourself, but also do not make your contribution more informative than is required (Grice, 1975). On Twitter, if you rarely send out tweets, it is unlikely that you'll have many followers. But if you send out tweets too frequently, followers flooded by your tweets are also likely to abandon you as well. Mueller & Stumme (2017) reported a negative relationship between inactive days of accounts and the number of followers for Twitter accounts. On the one hand, consistent tweeting frequency is important for attracting and keeping followers (Thoring, 2011). On the other hand, too much tweeting may lead to information overload and less social media engagement (Bontcheva et al., 2013). Thus, we should expect to see a curvilinear relationship between tweets per day and follower counts.

H2: There is an inverted U-shape relationship between tweets per day and follower counts.

Relevance

Relevance refers to the relationship between an information object and an information need (Bradford, 1934). Twitter Consumer Survey of Nielson (2013) shows that 53% of people following brand want to be notified of special offers and promotions; 51% hope to stay up to date with brand news, 44% desire to learn about new products and services, and 30% like to have access to exclusive content. Thus, relevance in Twitter means meeting follower's information needs by providing them with the content they're looking for. Relevant information leads to higher levels of perceived usefulness and ease of use, and higher user satisfaction, and ultimately, intentions to use the system (Hong et al., 2002). Therefore, relevant information could not only help retain current followers, but also contribute to follower growth. Hence, the more relevant the information, the more followers you'll have.

H3: Tweets' relevance is positively related to brands' Twitter account's follower counts.

Manner

The Maxims of manner requires messages to be clearly expressed or presented. Obscurity of expression and ambiguity should be avoided. Messages should be brief and orderly (Grice, 1975). In twitter, the Maxim of manner could be applied to the appearance of tweets. As tweets are a blend of messages and symbols such as #, and links to other resources, the presentations of tweets can vary from easily readable to needing efforts to decipher. Although hashtags and links offer great benefits such as easy categorization and discoverability, usage of these tools amongst Tweet contents also makes the presentation of the tweets less clean and tidy. Hutto et al. (2013) conducted research over 522,368 tweets and found that on average, hashtags were used in about 26% of total tweets and there was a strong negative relationship between hashtag ratio and number of followers, confirming the importance of Tweet presentation to attract followers. Therefore,

H4: The use of hashtags and links is negatively related to brands' twitter account followers.

The Social Network Perspective

Interactivity

From a social network perspective, two factors are examined for their influences on brand twitter account followers. The first one is interactivity with followers. Twitter provides organizations the ability to engage with the public and relationship-building communication channel that has been missing from websites. Kaplan and Haenlein (2010) viewed social media as "all about sharing and interaction" and urged business to ensure that "you engage in discussions with your customers". Lovejoy, Waters & Saxton (2012) suggested that Twitter's interactive messages like replies and mentions can assist organizations in communicating with other users. Saffer, Sommerfeldt & Taylor (2013) found that high organizational Twitter interactivity positively affects the perceived organization–public relationship of individuals. On Twitter, there are two commonly used methods of interacting with followers: user mention and reply. Therefore, higher interactivity in the forms of replies and mentions on Twitter by brands should be positively related to their follower counts.

H5: High interactivity in the forms of replies and mentions are positively related to brands' Twitter account's follower counts.

Social Learning

Learning is important to gain new followers. Levin et al. (2015) found that actively learning from past account history is an effective way to attract followers. However, learning is not restricted to learning from one's own history. On Twitter, brand Twitter accounts can not only broadcast messages to their followers, but also follow other brands of interest, such as suppliers or competitors, celebrities, news agencies, and opinion leaders, etc. By following other accounts, businesses form social networks via out-bound connections that facilitate information sharing (Quercia, Capra & Crowcroft; 2012) Businesses often want to find groups of related or similar social entities to follow. Twitter and other social media have become important new resources for social learning (Greenhow & Robelia, 2009). Walmart, for example, followed Cover Girl, Huggies, Oral-B, Bounty, and a number of other suppliers. By following each other, brands form a social network on Twitter and are kept abreast of the updates and trends from the accounts they follow. The social learning theory (Bandura, 1977) states that people can acquire new patterns of behavior by observing the behavior of others. Through observational learning, individual behaviors can spread across the population through a diffusion chain. Similarly, Bikhchandani, Hirshleifer & Welch (1998) argue that social learning leads to conformity, the rise of fads and information cascade. People learn by observing each other for several possible reasons: 1) positive payoff externalities, which lead to conventions such as driving on the right or left side of the road; 2) preference interactions, as with everyone desiring to wear "fashionable" clothing as determined by what others are wearing; and 3) sanctions upon deviants, as with a dictator punishing opposition behavior (Bikhchandani et al., 1998). On Twitter, social learning could be achieved and gauged by following and observing what others do and adjust one's twitting behaviors accordingly. The more accounts one follows, the more information one is exposed to, and the easier it is to get the latest trends and topics.

H6: Social learning by brand twitter accounts is positively related to brands' Twitter account's follower counts.

METHODS

Data Collection

We adopted a mix data collection approach as our required data came from different sources. First, for Twitter-related data, we directly collected the data for this study using Twitter.com and Twitonomy.com, an online Twitter analytics website. Second, we also relied on secondary data as we studied the verified brand Twitter accounts for Global 500 Brand from Brand Finance (www.brandirectory.com), an independent brand valuation and strategy consultancy headquartered in London, with presence in over 20 countries. We chose Global 500 Brand as it allows us to control for brand equity's influence on Twitter followers. These brands span across 49 industries and include companies such as Coca Cola, BP, Google, Volvo, and Accenture. For brands with multiple Twitter accounts (for example, Walmart, Walmart Labs, Walmart Newsroom), we chose the official and general-purpose one (Walmart). Of the 500 brands listed, excluding those without a verified English Twitter account, we had a final usable sample of 346 Twitter accounts spanning 48 industries from 31 countries. For robust results, we collected follower counts twice, once in 2014 and once in 2015, to purposefully examine the longitudinal effects of Twitter activities. By tracking follower counts at the time of the data collection and one year later, we were able to derive a causal relationship between Twitter activities and follower counts.

We collected brand value in 2014, brand industry and country data from Brand Finance. Brand Finance calculated brand values using the Royalty Relief methodology which determines the value a company would be willing to pay to license its brand as if it did not own it. Brand Twitter follower counts were collected twice, once in March 2014 and one year later, March 2015 from Twitter.com. The number of accounts followed in March 2014 was also collected from Twitter. Finally, Twitter activity data for the most recent 3200 Tweets up till March 2014 were collected from Twitonomy.com and included tweets per day, percentage of tweets that are re-tweets of others contents (i.e., non-original contents), average numbers of user mentions per tweet, percentage of replies in the total analyzed tweets, average number of links per tweet, average number of hashtags per tweet, and percentage of tweets favorite by others.

Variables

We operationalized the variables using the data discussed above. The dependent variable is follower count, both in March 2014 (afterward, FC_{2014} is used to represent the follower count in March 2014) and one year later in March 2015 (FC_{2015} is used to represent follower count in March 2015). Following Kwak et al. (2011), the quality of Tweets (quality) was assessed by the percentage of Tweets that receive "Favorite" from followers, as the number of "Favorite" (notation; *FAV*) indicates liking and approval of the content from users. Quantity of Tweets was measured by the average number of tweets brand Twitter accounts send out per day (notation; *TPD*). As Hypothesis 2 proposes a curvilinear relationship between quantity of Tweets and follower count, we included both quantity and quantity square in the model. Relevance was gauged by the percentage of original tweets, which is obtained by deducting the percentage of tweets that are re-tweets of others' contents from 100% (notation; 1-*RET*). We used two indices for manner: average number of links per tweet (notation; *LPT*) and average number of hashtags per tweet (notation; *HPT*), as these two have great influences on the presentation of tweets.

There are two social network-related constructs: interactivity and social learning. Average numbers of user mention per tweet (notation; *MPT*) and percentage of replies (notation; *RP*) in the total analyzed tweets were used to measure interactivity (notation; *ZS*). Since these two are highly correlated (0.74), we averaged the z scores of these two as an index of interactivity. Social learning was measured by the number of other accounts the brand corporate accounts follow (notation; FO).

For control variables, we included brand value (notation; *BV*) in 2014 as a control variable in the model since the more value a brand has, the more likely people are willing to follow it. Controlling for brand value would enable us to discover unique activities on Twitter that lead to more followers. We also controlled for industry and used 5 dummy variables for 6 industries (Finance and insurance (notation; I_1), manufacturing (notation; I_2), information (notation; I ; information industry was the baseline for the 5 dummy variables [0,0,0,0,0]), services (notation; I_4), transportation and warehousing (notation; I_5), others (notation; I_3)) according to U.S. census industry categorization guidelines. Geographic locations of the companies (Africa (notation; A_1), America (notation; A_2), Asia (notation; A), Europe (notation; A_3) and Oceania (notation; A_4)) were also included in our analysis as control. Here, the 4 area dummy variables will be used for 5 areas and Asia was set as [0,0,0,0].

5. ANALYSIS AND RESULTS

Table 1 and Table 2 summarized the descriptive statistics of all the variables and their correlation matrix.

The average brand value for the 346 brands was around 8000 million U.S. dollars. The average follower count was around 400,000 for 2014, and 600,000 a year later. Brands on average followed 6,188 other Twitter accounts, sent out 16 tweets a day, and averaged 0.62 user mentions, 0.56 hashtag, and 0.39 link per tweet. 35.6% of the tweets were replies, and average, 36% of tweets were favorited.

Multiple regression was used to analyze the relationships between variables with SPSS. SPSS is one of the most popular software packages geared towards statistical analysis and data mining (Verma, 2012). Since regression analysis is based on the minimization of squared error, a few extreme observations can exert a disproportionate influence on parameter estimates. Our data set, unfortunately, has strongly skewed distributions (i.e. the absolute value of skewness and kurtosis greater than 2), for follower counts, following, brand value, tweets per day, average hashtags and retweets percentage. Thus, we performed a log ten transformation of these variables to achieve normality and homoscedasticity (Hair et al., 2006) and reran the analysis. We performed hierarchical multiple regression analyses so that the contribution of each set of variables to the dependent variable can be seen and model comparison can be achieved. For the i -th company ($i = 1,..,346$) in the k -th period (e.g., $k \in (2014, 2015)$), we tested a total of five models: Model 0 (baseline model) included only the control variables, while Model 1 to Model 4 had a mix of combination of the proposed variables and control variables. Model 1 included only the variables from our hypotheses (the mathematics equation can be found in Model (1)); we added brand equity along with our research variables in Model 2; in Model 3, industry information was additionally controlled for; finally, in the Model 4, geographic area info was introduced besides all the other variables. The results are reported in Table 3 and Table 4 below:

Table 1. Descriptive statistics

	N	Mean	Std. Deviation	Median	Skewness	Kurtosis
Follower count 2015 (FC_{2015})	346	594398.84	1776670.62	97180.00	5.76	40.36
Follower count 2014 (FC_{2014})	346	397456.27	1296879.50	51393.00	6.30	48.06
Following (FO)	346	6188.73	32153.40	768.50	14.29	231.40
Brand value (BV ; in millions of USD)	346	7956.47	7985.60	4659.00	2.87	10.38
Tweets per day (TPD)	346	16.42	43.19	4.38	6.93	66.06
User mentions per tweet (MPT)	346	0.62	0.33	0.64	0.07	-0.08
Replies % (RP)	346	35.61	32.80	23.36	0.63	-1.06
Links per tweet (LPT)	346	0.39	0.24	0.04	0.42	-0.61
Hashtags per tweet (HPT)	346	0.56	0.46	0.47	1.69	4.96
Retweets % (REP)	346	11.07	11.84	7.93	1.80	4.54
Favorited % (FAV)	346	36.00	22.43	32.97	0.60	-0.27
Industry		Percentages				
Finance and Insurance	59	17.05%				
Information	62	17.92%				
Manufacturing	116	33.53%				
Services	29	8.38%				
Transportation and Warehousing	22	6.36%				
Others	58	16.76%				
Area						
Africa	1	0.29%				
America	182	52.60%				
Asia	48	13.87%				
Europe	109	31.05%				
Oceania	6	1.73%				

Table 2. Correlations among variables

	FC_{2015}	FC_{2014}	FO	BV	TPD	MPT	RP	LP	HP	REP	FAV	I_1	I_2	I_3	I_4	I_5	A_1	A_2	A_3	A_4
FC_{2014}	.97**																			
FO	.16**	.19**																		
BV	.16**	.16**	.02																	
TPD	.11*	.12*	.26**	.04																
MPT	.04	.04	.19**	.07	.35**															
RP	.02	.03	.20**	.04	.46**	.76**														
LP	-.07	-.08	-.14*	.00	-.21**	-.35**	-.58**													
HP	-.08	-.09	-.08	.02	-.21**	-.18**	-.39**	.30**												
REP	.23**	.22**	-.05	.10	-.30**	-.30**	-.58**	.60**	.38**											
FAV	.44**	.42**	.08	.20**	-.09	.02	-.17**	.28**	.27**	.78**										
I_1	-.11*	-.11*	-.06	.03	-.10	-.13*	-.04	.08	-.09	-.08	-.19**									
I_2	-.08	-.08	.06	-.09	-.05	.01	.01	-.14**	.03	.05	.02	-.32**								
I_3	.03	.03	.00	.00	.04	.08	.16**	-.06	-.01	-.01	.07	-.20**	-.32**							
I_4	-.02	-.03	-.04	.00	-.03	.04	-.05	.12*	.15**	.09	.09	-.14*	-.21**	-.14*						
I_5	-.07	-.06	-.03	-.02	.08	-.04	-.04	-.02	-.02	-.07	-.10	-.12*	-.19**	-.12*	-.08					
A_1	-.01	-.01	-.01	-.02	.00	.03	.03	-.05	-.03	-.02	-.03	-.02	-.04	-.02	-.02	-.01				
A_2	.13*	.14**	.08	.05	.06	.20**	.09	.01	-.02	.13*	.23**	-.03	-.15**	.07	.04	.01	-.06			
A_3	-.08	-.09	-.04	-.04	-.01	-.14**	-.09	.12*	.12*	.05	-.06	.09	.10	-.02	-.03	-.07	-.04	-.71**		
A_4	-.04	-.04	-.01	-.05	.06	.13*	.20**	-.14*	-.14*	-.20**	-.14**	.18**	-.09	.00	-.04	-.03	-.01	-.14**	-.09	

PS1: **. Correlation is significant at the 0.01 level (2-tailed) and at the 0.05 level (2-tailed). N=346
PS2: *LP*= Links %; *HP*=Hashtags %

$$\log(FC_{k,i}) = \beta_{0,k} + \beta_{9,k}(BV_i) + \beta_{10,k}(I_{1,i}) + \beta_{11,k}(I_{2,i}) + \beta_{12,k}(I_{3,i}) + \beta_{13,k}(I_{4,i}) + \beta_{14,k}(I_{5,i}) + \beta_{15,k}(A_{1,i}) + \beta_{16,k}(A_{2,i}) + \beta_{17,k}(A_{3,i}) + \beta_{18,k}(A_{4,i}) + \varepsilon_i \quad (0)$$

$$\log(FC_{k,i}) = \beta_{0,k} + \beta_{1,k}\log(FO_i) + \beta_{2,k}\log(TPD_i) + \beta_{3,k}TPD_i^2 + \beta_{4,k}LPT_i + \beta_{5,k}HPT_i + \beta_{6,k}FAV_i + \beta_{7,k}\log(1 - RET_i) + \beta_{8,k}(ZS_i) + \varepsilon_i \quad (1)$$

$$\log(FC_{k,i}) = \beta_{0,k} + \beta_{1,k}\log(FO_i) + \beta_{2,k}\log(TPD_i) + \beta_{3,k}TPD_i^2 + \beta_{4,k}LPT_i + \beta_{5,k}HPT_i + \beta_{6,k}FAV_i + \beta_{7,k}\log(1 - RET_i) + \beta_{8,k}(ZS_i) + +\beta_{9,k}(BV_i) + \varepsilon_i \quad (2)$$

$$\log(FC_{k,i}) = \beta_{0,K} + \beta_{1,K}\log(FO_i) + \beta_{2,K}\log(TPD_i) + \beta_{3,K}TPD_i^2 + \beta_{4,K}LPT_i + \beta_{5,K}HPT_i + \beta_{6,K}FAV_i + \beta_{7,K}\log(1 - RET_i) + \beta_{8,K}(ZS_i) + \beta_{9,K}(BV_i) + \beta_{10,K}(I_{1,i}) + \beta_{11,K}(I_{2,i}) + \beta_{12,K}(I_{3,i}) + \beta_{13,K}(I_{4,i}) + \beta_{14,K}(I_{5,i}) + \varepsilon_i \quad (3)$$

$$\log(FC_{k,i}) = \beta_{0,k} + \beta_{1,K}\log(FO_i) + \beta_{2,k}\log(TPD_i) + \beta_{3,k}TPD_i^2 + \beta_{4,k}LPT_i + \beta_{5,k}HPT_i + \beta_{6,k}FAV_i + \beta_{7,k}\log(1 - RET_i) + \beta_{8,k}(ZS_i) + \beta_{9,k}(BV_i) + \beta_{10,k}(I_{1,i}) + \beta_{11,k}(I_{2,i}) + \beta_{12,k}(I_{3,i}) + \beta_{13,k}(I_{4,i}) + \beta_{14,k}(I_{5,i}) + \beta_{15,k}(A_{1,i}) + \beta_{16,k}(A_{2,i}) + \beta_{17,k}(A_{3,i}) + \beta_{18,k}(A_{4,i}) + \varepsilon_i \quad (4)$$

Overall, the baseline model (Model 0) has an R squared of 24%, meaning that our control variables, i.e., brand value, geographic location, and industry together explained 24% of total variances in follower counts. The proposed model (Model 4) has an R squared of 0.76, meaning that 76% of variances in follower counts could be explained by our model, indicating a good model fit. The hypotheses-only model (Model 1) without all the control variables along explained about 74% of total variances. Geographic locations did not seem to impact the number of followers in the final model while being in certain industries (such as manufacturing and finance) attracts fewer followers than the benchmark industry (information technology). Brand value, as expected, was positively related to follower counts.

The results supported H1, with quality of tweets measured by percentage of tweets favorited significantly related to both follower counts in 2014, and a year later in 2015, highlighting the importance of quality of content in brand Twitter accounts.

H2 argued a curvilinear relationship between tweets per day and follower counts. The results indicated that tweets per day was positively related to follower counts, and tweets per day squared was negatively related to follower counts (b= -0.17 and -0.21 for 2014 and 2015 follower counts). We plotted a graph to clarify the pattern of such a curvilinear relationship for the original data in 2014 (see Figure 3). The graph shows that as the number of tweets per day increases, follower counts decrease for the original data set. Thus, H2 received support.

H3 posited that tweets' relevance measured by the percentage of original content is positively related to brand Twitter account's follower counts. This hypothesis was not substantiated.

H4 argued that the use of hashtags and links could be negatively related to follower counts. The results supported this hypothesis, with a significant negative relationship between manners and follower counts in both years.

For H5, interactivity with followers in the forms of replies and mentions is not significantly related to brands' Twitter account's follower counts. Thus, H5 was not supported.

Finally, H6 received support. Social learning measured by the number of accounts followed is positively related to brands' Twitter account's follower counts. However, the effects of social learning seem to wear out within a year: it was only significant for 2014 (b=0.10) but was no longer effective a year later in 2015.

Table 3. Hierarchical multiple regression results with log ten transformed data 2014

Independent	Dependent Variable: $\log(FC_{2014})$				
	Model 0	Model 1	Model 2	Model3	Model 4
Intercept	1.13(0.59)	5.26***(0.80)	3.91***(0.88)	4.34***(0.89)	4.24***(0.90)
Brand Value					
$\log(BV)$	0.29***(0.15)		0.10***(0.29)	0.09***(0.09)	0.09***(0.09)
Industry					
I_1	-0.34***(0.15)			-0.10***(0.09)	-0.10***(0.09)
I_2	-0.16**(0.13)			-0.12***(0.08)	-0.12***(0.08)
I_3	-0.07(0.15)			-0.03(0.09)	-0.04*0.09)
I_4	-0.09(0.19)			-0.07**(0.11)	-0.08**(0.11)
I_5	-0.15***(0.21)			-0.05(0.12)	-0.05(0.12)
Country					
A_1	0.02(0.85)				0.00(0.48)
A_2	0.40***(0.14)				0.01(0.08)
A_3	0.24***(0.15)				0.04(0.09)
A_4	0.08(0.37)				-0.02(0.22)
Social learning					
$\log(FO)$		0.12***(0.03)	0.11***(0.03)	0.10***(0.03)	0.11***(0.03)
Quantity					
$\log(TPD)$		0.34***(0.06)	0.33***(0.06)	0.29***(0.06)	0.29***(0.06)
TPD^2		0.04(0.00)	0.04(0.00)	0.05(0.00)	0.05(0.00)
Manner					
LPT		-0.11***(0.14)	-0.11***(0.14)	-0.10***(0.14)	-0.11***(0.14)
HPT		-0.13***(0.06)	-0.13***(0.06)	-0.12***(0.06)	-0.13***(0.06)

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Table 3. Continued

Independent	Dependent Variable: $\log(FC_{2014})$				
	Model 0	Model 1	Model 2	Model3	Model 4
Quality					
FAV		0.70***(0.00)	0.68***(0.00)	0.68***(0.00)	0.68***(0.00)
Relevance					
$\log(1-RET)$		-0.08**(0.42)	-0.06**(0.42)	-0.07**(0.42)	-0.07**(0.42)
Interactivity					
ZC		0.01(0.03)	0.01(0.03)	0.03(0.03)	0.03(0.03)
R square	0.24	0.74	0.75	0.76	0.76
Adjusted R square	0.22	074	0.74	0.75	0.75

PS: ** is significant at the 0.01 level (2-tailed) and ** is significant at the 0.05 level (2-tailed).

DISCUSSION AND CONCLUSION

Summary of Findings

Although the importance of social media has been increasingly recognized, little research has been conducted to explore what attracts people to follow brand twitter accounts. The current research addressed this gap in the literature and the results show that the frequency and quality of the tweets, Tweeting manner, as well as social learning all contributed to follower counts. Specifically, the quality of tweets is the most important factor leading to follower counts, followed by the frequency of tweets. Lack of manners in tweets with too many hashtags and links could lead to negative impacts in follower counts, while social learning through following others could facilitate follower growth in the short run.

Discussion

First, the results highlighted the importance of quality content in attracting followers on Twitter. This echoes with prior research that identified Twitter as a media more than a social network. Kwak et al. (2010) obtained 41.7 million user profiles, 1.47 billion social relations, 4,262 trending topics, and 106 million tweets by crawling Twitter and found that the majority (over 85%) of topics are headline news or persistent news in nature. Thus, it is quality content, rather than social interactions, that are the backbone of Twitter, and the key driver for follower counts. With this insight in mind, the finding that interactivity is not positively related to follower counts is understandable, as most followers treat Twitter as a source of news and information, rather than means of interaction and networking with brands. Thus, high interactivity of brands published on brands' timelines actually distracts and drives followers away, as reading interactions between the brand and its followers may not usually be considered as quality content.

Another interesting finding is that followers don't seem to care whether the tweet is from the brand or retweeted content, as relevance is not positively related to follower counts. Possibly it is because they care more about the quality of the content. Even if it's a retweet, as long as it's interesting, they do not turn away.

Quantity of tweets has a curvilinear relationship with follower counts. This confirms the maxim of quantity: you should provide enough messages to explain yourself, but also do not make your

Table 4. Hierarchical multiple regression results with logten transformed data 2015

	Dependent Variable: $\log(FC_{2015})$				
	Model 0	**Model 1**	**Model 2**	**Model3**	**Model 4**
Intercept	1.16**(0.60)	5.63(0.79)	4.12(0.87)	4.54(0.88)	4.50(0.90)
Brand Value					
$\log(BV)$	0.30***(0.30)		0.11***(0.09)	0.10***(0.09)	0.10***(0.09)
Industry					
I_1	-0.30***(0.16)			-0.05(0.09)	-0.05(0.09)
I_2	-0.11(0.14)			-0.06(0.08)	-0.07(0.08)
I_3	-0.04(0.16)			-0.01(0.09)	-0.01(0.09)
I_4	-0.09(0.19)			-0.08***(0.11)	-0.08***(0.11)
I_5	-0.14***(0.21)			-0.04(0.12)	-0.04(0.12)
Country					
A_1	0.04(0.86)				0.01(0.47)
A_2	0.38***(0.14)				0.00(0.08)
A_3	0.22***(0.15)				0.02I(0.09)
A_4	0.08(0.38)				-0.02(0.21)
Social learning					
$\log(FO)$		0.05(0.03)	0.04(0.03)	0.04(0.03)	0.04(0.03)
Quantity					
$\log(TPD)$		0.37***(0.06)	0.37***(0.06)	0.35***(0.06)	0.35***(0.06)
TPD^2		-0.05(0.00)	-0.05(0.00)	-0.05(0.00)	-0.05(0.00)
Manner					
LPT		-0.15***(0.14)	-0.14***(0.14)	-0.14***(0.14)	-0.14***(0.14)
HPT		-0.10***(0.06)	-0.10***(0.06)	-0.09***(0.06)	-0.09***(0.06)

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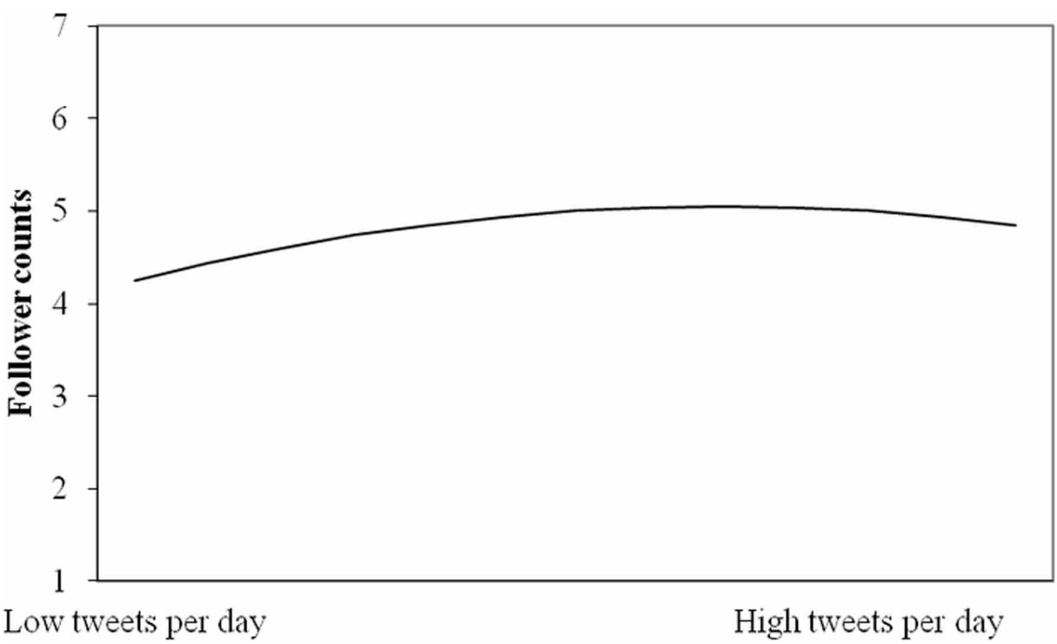
Table 4. Continued

	Dependent Variable: $\log(FC_{2015})$				
	Model 0	Model 1	Model 2	Model3	Model 4
Quality					
FAV		0.72***(0.42)	0.70***(0.00)	0.70***(0.00)	0.70***(0.00)
Relevance					
$\log(1 - RET)$		-0.07**(0.42)	-0.06*(0.41)	-0.07**(0.42)	-0.07**(0.42)
Interactivity					
ZC		0.02(0.03)	0.01(0.03)	0.03(0.03)	0.03(0.03)
R square	0.23	0.75	0.76	0.76	0.76
Adjusted R square	0.20	0.74	0.75	0.75	0.75

PS: ** is significant at the 0.01 level (2-tailed) and ** is significant at the 0.05 level (2-tailed).

Figure 3. Pattern of curvilinear relationship between tweets per day and follower counts



contribution more informative than is required. Therefore, there is this intricate balance of providing enough messages, but not too many messages.

Finally, contrary to public belief that hashtags help your tweets get discovered and are thus beneficial for your follower counts, the results showed that hashtags and links are both negatively related to follower counts. Although hashtags and links add a wealth of information to tweets and expand the limits of the 280 characters count, it seems that they also add difficulty in reading tweets and drive followers away.

Looking at both data sets with both 2014 and 2015 follower data, we could see that the results are quite consistent for the year sampled, and one year later, even though the average follower count had a 50% increase over the year. This may be due to the consistency in the style of operation for brand Twitter accounts, but it also may signal the unique feature of social network: quality content is shared by one follower to his or her network, then someone in that network likes it and share again... and the sharing goes on and on as time goes by. Thus, a good tweet goes a long way on Twitter. The influence of tweets extends beyond the hour and the day it was published, but rather lives as long as it is being shared, favorited, and commented on.

Theoretical Contribution

This study aims to contribute to social media regarding brands' Twitter activities. Compared with other research on Twitter follower counts (e.g., Hutto et al., 2013; Mueller & Stumme; 2017), we have several advantages. First, we specifically examined brands' Twitter activities, while the other studies focused on Twitter accounts in general. Second, we offer a parsimonious model (with only 6 key variables, compared with over 20 variables in other research) that explained a high percentage of variances in the dependent variable. We contribute to Twitter research in several ways. First, by building on the foundation of Grice's Maxims (Grice, 1975) and features of social networks, this research provided a theoretical framework to understand the context of brands' Twitter accounts. It clarified what factors contribute to follower counts in the context of high-value brands. The results showed that the quality and frequency of the tweets, the Tweeting manner, as well as social learning all play a role in follower counts.

Second, the proposed model has established the importance of the communication perspective on Twitter in attracting followers. Twitter, with its dual nature that combines both social interaction/social networks and news media (Fischer& Reuber, 2011; Kwak et al., 2010), sometimes causes confusion to corporations as to whether to treat it as a media or a social network. This research confirmed prior findings that Twitter is, by and large, a news media. Whereas most prior research has focused on the social network nature of Twitter, the results of this research indicated that the communication perspective of Twitter also warrants attention.

Finally, this study clarified some of the myths about Twitter follower counts on the internet with theory-guided tests. The results showed that contrary to popular belief, hashtags and links may not always work in your favor. Additionally, interactivity with some followers published on timelines can drive other followers away. The findings help provide a systematic overview that enriches extant social media literature while providing insights into the important factors contributing to Twitter follower counts.

Practical Implication

The findings of this study can help brand Twitter managers gain a better understanding of how to attract followers on Twitter. Based on the findings, we offer the following recommendations for practice.

First, Focus on the quality of content. The results indicated that of all the factors, the quality of the content has the highest impact on follower counts. Thus, brand Twitter managers should focus on providing quality content to their followers. They can examine their history and find out what type of tweets are most liked and shared, and provide more similar content. In addition, they can also learn from others: studying their competitors and see their most shared and liked contents, and derive insights from there as well.

Second, don't publish every interaction with customers. Although Twitter is often used for interacting with customers, it may not always be necessary to publish every interaction on the brands' Twitter timeline and let everybody see it. If possible, interaction with specific customers can take the form of private messaging, so that only those involved will see the reply, without bombarding other followers with conversational tweets. Some companies separate customer service with general-purpose Twitter accounts, for example, Bank of America news, and Bank of America customer service. This may also be a sensible way to manage a brand's Twitter account.

Third, Tweet often, but not too much. The results indicated an inverted U shape relationship between tweets per day and follower counts. Thus, as tweets per day increase, brand twitter accounts gain more followers at first, and then, as the number of tweets keeps increasing, followers begin to leave. There is an intricate balance to keep in tweets per day. The majority of brands' Twitter accounts send out less than 10 tweets per day, which could be a good range to start with.

Fourth, use hashtags and links wisely. Hashtags and links help increase discoverability and information content, but they also render the content of tweets less readable. Therefore, brand Twitter managers should use caution when use hashtags and links. It would be helpful if the hashtags and links are not mixed along with the content, but rather, put at the end of the tweets so that the readability of the tweets is improved.

Finally, learn from the leaders. The findings indicated that the more accounts a brand follows, the more followers it gains. Following other accounts keep brand Twitter managers up with the latest development, popular trends, and hot topics. Thus, managers need to embrace the opportunity of learning from others by following other accounts on Twitter that are relevant to their brand or industry.

Limitation and Future Research

There are several limitations in this research that present opportunities for future research. First, although the sample of 346 companies from the Global 500 Brand, each with up to 3200 tweets is sufficiently diverse to support the findings, the results are not tested against companies with small and medium brand value. We expect the model to still hold for all kinds of companies. Future studies could sample a larger set of companies to include small and medium-sized brands. Second, the generalizability of our findings is limited to Twitter accounts that operate in English, catering to the English speaking audience. Future research could explore Twitter accounts that use languages other than English, and explore the role of culture in Twitter follower counts. A third limitation is that our measures for quality, relevance, manner and social learning are quantitative surrogates and not direct measures of these constructs. Although using data from Twitter and Twitter analytics site has the advantage of providing an objective, data-driven approach, direct measuring of the constructs can give us richer information and dimensional knowledge about the constructs. Thus, future research could benefit from user surveys to further understand the question.

CONCLUSION

Practitioners and researchers increasingly recognize the important role social media plays in building brands and communicating with customers. This study is one of the first attempts to develop a theory on brands' Twitter followers by adopting both the communication and social network perspectives in the context of brand Twitter account. Our results revealed that the quality and frequency of tweets, presentation manner, and social learning all contributed to follower counts. With an understanding of the major contributing factors to Twitter follower counts, these results serve as a basis for future theoretical development in the area of social media marketing, which in turn, could also yield valuable insights that guide practice.

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