Is it True?: The Effect of Message Source and Valence on the Rebroadcasting of Online Rumors

(Working Paper)

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Motivation

In a recent State Farm commercial, a young woman tries to explain to her male friend, that she looks to the Internet as her main source of information, using the rationale of "I saw it on the Internet, it must be true." While the advertisement may have had sarcastic purpose, the young woman's rationale, which is far from the truth, gives light to a harsh reality. Consumers are looking to the Internet more and more as a source of information about politics, sports, and brands. We live in age where people trust the Internet as a news source as much as other media, (Flanagin and Metzger, 2000). But this trust is compromised increasingly by user-generated content, which gives Internet users the opportunity to post anything, truth, or not. And as a result the lines between truth and falsehood can be blurred, presenting a problem not only for consumers who are searching for factual information, but also presenting a communication dilemma for not only news organizations, but brands as well. No longer do brands have dominant control over their messaging; the content as it relates to a brand, and the subsequent value of that brand is co-created by consumers. The possible dissemination of false information or unwanted associations could prove to be detrimental to a brand's value and image.

Particularly, user generated content platforms, such as Facebook and Twitter, give users the opportunity to post false information, which can be further reposted or "rebroadcasted" to other users. Sometimes these falsehoods can start as rumors. Rumors can be defined as "an unverified account or explanation of events circulating from person to person and pertaining to an object, event, or issue in public concern" (Peterson, 1951). A recent examination of some of Google's real-time search results for Twitter revealed that real-time information was mostly "fabricated content, unverified events, lies and misinterpretation" (Metaxas and Mustafaraj, 2010). For this reason many user-generated content platforms are considered collective rumor mills that propagate misinformation, gossip, and, in extreme cases, propaganda (Leberecht 2010).

Brands would not want false rumors about them online, so how should firms deal with them? The problem is even more of a conundrum in that when confronted with a rumor in a user-generated content platform, consumers generally do not know whether to believe the rumor is true or false. Much effort is spent on stigmatizing rumors as well as the sender as opposed to clarifying their source (Kapferer, 1990). This can become a problem not only for brands in the traditional since of firms, but also with brand of celebrities, brands of political organizations, and non-profits. For the purposes of this research I examine two aspects of a rumor on Twitter that may influence what a social media user believes and ultimately what they rebroadcast or share: the credibility of the rumor source and furthermore what is the valence of the content of the message.

Background

Rumors

Rumors can be defined as "an unverified account or explanation of events circulating from person to person and pertaining to an object, event, or issue in public concern" (Peterson, 1951). Key to the belief attached to rumors is their diffusion through word of mouth communication. Unlike firm-generated marketing, word-of mouth communication is not controlled by the firm. And this non-firm generated content often includes negative content because consumers often use word of mouth to express dissatisfaction (Swan & Oliver, 1989). Hence, firms are particularly concerned about negative word-of mouth particularly when there is no evidence of its being true-that is, when it is a rumor. While research has been done on the diffusion process of products (Arndt 1967), the diffusion of innovations (Gatignon and

Robertson 1985), urban legends (Donavan et al,1999) through word of mouth communication, research regarding the diffusion of rumors is limited.

Research on rumors began in sociology looking at the affect of rumors during World War II on of soldiers and the population at large (Allport & Postman, 1947). However, this research did not examine rumors in marketplace settings. Few research studies examine factors influencing the diffusion of rumors by consumers. Studies have examined the effects of product trial on consumers' likelihood of spreading word-of-mouth information (TARP, Inc., 1985), but not the likelihood of relaying non-trial-based rumors. Other studies have examined the credibility of consumers' messages and their impact on repurchase intentions (e.g., Herret al., 1991), but not factors influencing the diffusion of these messages. Some research has considered consumer evaluation of rumors, finding that consumers attach a lower importance, lower credibility, and negative attitudes to rumors as compared to other sources of product information (Kamins, 1997). There has been some research on rumors that considers the context in which rumors may be more likely to be spread. For instance, the emergence and diffusion of rumors depends on the social context and the groups involved; members of competing groups are more willing to spread rumors about competing products (Thompson and Ward, 2008). But none of the research examining the factors that influence the diffusion of rumors has looked at message source or valence.

Theoretical Development and Hypotheses

Rebroadcasting Behavior

Rebroadcasting is a specific type of online word of mouth behavior, in which an online user shares a message with others in a particular online environment. A number of studies have examined factors that influence online word-of-mouth behavior. For instance, Hennig-Thurau et al (2004) found that consumers' desire for social interaction, desire for economic incentives, concern for other consumers, and the potential to enhance their own self-worth are the primary factors leading to rebroadcasting behavior. But the extent to which this research considers the rebroadcasting of rumors, offers very little depth.

Source Credibility

When considering the rebroadcast behavior of a particular message, it is useful to consider the source of that message. Source credibility refers to a recipient's perception of the credibility of a message source; it is not concerned with the content of the message itself (Chaiken, 1980). Source credibility has consistently been identified as an important cue in informational influence process (Pornpitakpan, 2004). It is also a primary concern of consumers when engaging in online activities (Cheung et al., 2009). Source credibility has been shown to have a positive effect on message credibility (Chow et al., 1995). And message credibility has been shown to positively influence message sharing (Mendoza and Castillo, 2010).

Increased reliance on social media for news and information has made credibility a non-trivial concern (Mendoza and Castillo, 2010). When it comes to social media, users find news headlines significantly less credible when presented on Twitter (Schmierbach and Oeldorf-Hirsch, 2010). Some researchers have already worked on developing systems to automatically classify tweet credibility. And while some past research shows that users currently assess a tweet's credibility based on trust relationships with the sources of those messages (Mendoza and Castillo, 2010), little has been observed in regards to what happens when false tweets or rumors are shared and disseminated as truth. Therefore I propose:

H1: A user is more likely to share a Twitter rumor if the message source has high credibility.

Valence of Message Content

Previous research has also examined the role of message content on broadcasting behavior. One reason people may share news is because it just contains useful information. Consumers may also share useful content to help others or for self-enhancement purposes (Wojnicki and Godes 2008) or create reciprocity with others (Fehr, Kirchsteiger, Riedl 1998). Heath, Bell and Sternberg (2001) have shown that emotional content is more likely to be shared in social media environments. Specifically, content that fuels awe and anger are more likely to be shared (Berger and Milkman, 2012).

Past research on word of mouth communications, tells us that the volume of word of mouth has strong effects on behavior (Liu 2006), along with the valence of the message (Richins 1983). Customers with extreme levels of satisfaction or dissatisfaction are more likely to share experiences than customers with neutral opinions (Anderson 1998). Positive WOM is motivated primarily by the need for self-enhancement, and negative WOM is motivated by the need for self-affirmation (Alexandrov, et al 2013). The intention to help others and share social information affects only negative WOM. Berger and Milkman (2012) examined that positive content is more likely to go viral and be rebroadcasted than negative content. For example, an individual would prefer to be known as someone who shares upbeat stories or makes others feel good rather than someone who shares things that makes others angry or upset. Sharing positive content may also help boost others' mood or provide information about potential rewards (i.e., this restaurant is worth trying). There has been other literature that argues that negative word of mouth is more likely to be shared. Folkes (1984) found that people communicate more information about product and service failures than about successes. Kamins et al. (1997) suggest that stories about product failures (negative information) may be more vivid, thus strengthening further transmission of the story.

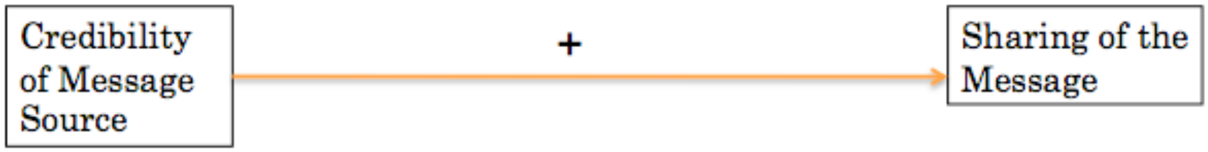
Regarding the valence of the rumors effect on their diffusion and rebroadcasting, not much research has been done. Consumers are exposed to significantly more negative rumors (92.6%) than positive rumors (7.4%). As Kamins et al. (1997) suggests that the primary reason for transmitting a rumor is self-interest. A positive rumor reflects positively on the self, while a negative rumor may be spread to downgrade a competitor. They found that consumers were exposed to and more likely to spread more negative than positive rumors.

I propose an interaction of rumor valence with source credibility. Interactional effects between valence and credibility have been observed in customer reviews (DeCarlo, 2001). The results indicated that a negative online review is deemed more credible than a positive online review, while a positive online review leads to a greater initial trust than a negative review. I propose similar results when looking at online rumors. I believe that when there may be some doubt about the credibility of a Tweet, as is the case with rumors, that the sender will be motivated by a need for self-affirmation. Therefore I propose that:

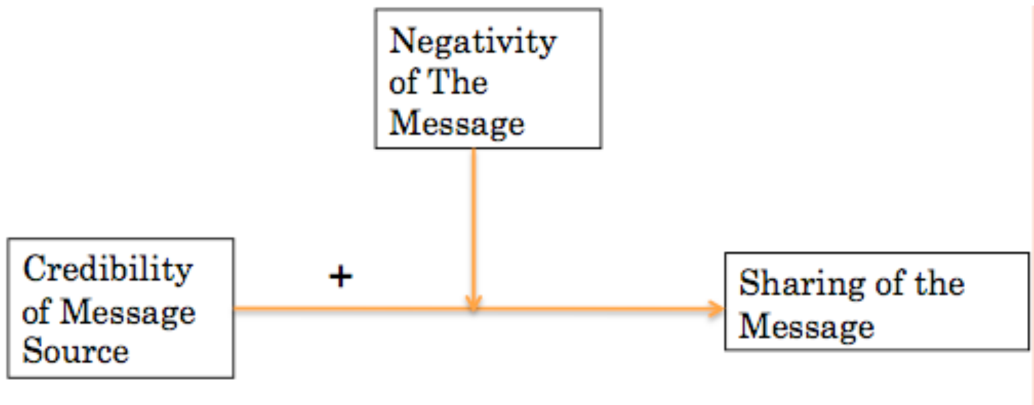
H2: If a tweet is negative, the user is more likely to share the message if the source is of low credibility (H2a). And if the tweet is positive, the user is more likely to share the tweet if the source is of high credibility (H2b).

Conceptual Model

Hypothesis 1



Hypothesis 2



Experimental Method

For the purposes of this testing this model I used a 2x2 experimental design. Each of 125 Mechanical Turkers were presented with one of four tweets about celebrity comedian/actor Kevin Hart (See Exhibit 1). The message was either positive ("Kevin Hart is getting married") or negative ("Kevin Hart has been arrested"). In the data this was recorded as a dummy variable with 0=positive message and 1=negative message. Additionally the source of the tweet was either a high credibility source (CNN) or a low credibility source (TMZ). TMZ is a gossip celebrity news website whereas CNN is a U.S. cable and online news network. This was also recorded as a dummy variable with 0=CNN and 1=TMZ. For each tweet, respondents were asked how likely they would be to share the message on a scale from 1 to 7 (1=Very Unlikely 7=Very Likely). Respondents were also asked if they believed the message was true (also on a scale from 1 to 7).

Manipulation checks were included in the survey to validate the accuracy of the two manipulations. One manipulation check was included to ensure that the positive and negative messages were distinguishable. Respondents were presented with the statement, 'This is a positive message". They then rated how much they agreed with the statement on a scale to 1 to 7 (1=Strongly Disagree 7= Strongly Agree). Another manipulation check was also included to ensure that participants viewed CNN as high credible source and viewed TMZ as a low credible source. Respondents were presented with four statements about the credibility of the message source. For each statement the respondent rated how much they agreed with the statement on a scale to 1 to 7 (1=Strongly Disagree 7= Strongly Agree). An average credibility score was computed from the responses.

Respondents were then asked several questions about their twitter usage (if they own a twitter account, how often they access the account, and how often they post). Demographic information, such as age and gender, was also collected from the respondents.

Results

Manipulation Check (see Exhibit 2)

One manipulation check ensured the validity of the experiment, while another created cause for concern. The positive/negative manipulation check validated that the "Kevin Hart is getting married" was viewed more positive than the "Kevin Hart has been arrested" message. Respondents found the positive message to be significantly more positive negative message (2.69 mean difference, p=.001, Exhibit 2). However, the credibility manipulation check did not ensure that there was a difference in credibility between TMZ (low credibility) and CNN (high credibility). On average, respondents found the CNN to not be significantly more credible than TMZ (.32 mean difference, p=.114, Exhibit 2).

Experiment

Of the 125 total respondents 74.4% of respondents were Twitter users and 25.6% were not Twitter users. On average, respondents found the positive message to be true more than the negative message (.756 mean difference, p=.001, Exhibit 3). But unfortunately, the results of the experiment did not support any of the hypotheses.

The first hypothesis stated that users would be more likely to share a false tweet if the message source has high credibility. In the experiment, users were actually more likely to share a message from a low credible source (.034 mean difference), but the difference was not significant (Exhibit 4). Running a simple regression, we can also see that there is a non-significant effect of credibility on the likeliness to share the message (p=.97). This means we fail to reject the null hypothesis that source credibility does not have an affect on a user's willingness to share a message. The predicted hypothesis (H1) is not confirmed.

The second hypothesis stated that if the tweet were negative, the user would be more likely to share the message if the source is of low credibility and if the tweet were positive, the user would be more likely to share the tweet if the source is of high credibility.

On average, negative messages were more likely to be shared from high credibility sources (.491 mean difference, Exhibit 5), but the difference was not significant (p=.33). Positive messages were actually more likely to be shared from low credibility sources (.558 mean difference), although this difference was also not significant (p=.26). To observe if the effect of credibility on the likeliness to get shared is moderated by the negativity of the message, an interaction variable credneg was introduced. From performing a regression (Exhibit 6), we see that this interaction term was not signification ($p=.14$) and that negativity does not have a significant moderating effect on credibility's effect on message sharing.

Even if we introduce some variables that represent Twitter usage into our regression, we get non-significant effects on the user's likeliness to share a message. Only if the variable fam is introduced (Which asks users how familiar they were with Kevin Hart?) into the regression, do we observe any significant effects (Exhibit 7). There is a significant relationship between the users familiarity with Kevin Hart and the likeliness to share the message ($p<.05$). Of the respondents, 46.4% were Very Unfamiliar, Unfamiliar, or Somewhat Unfamiliar with Kevin Hart, while 47.2% were Very Familiar, Familiar, or Somewhat Familiar with Kevin Hart.

Discussion

While much experience was gained from creating and engaging in this study, the results were not favorable. Most of the effects were not statistically significant and none of the proposed hypotheses were accepted. The one significant effect that did occur was the effect of subject familiarity on the user's willingness to share the message. This exhibits that users are more willing to share messages that contain familiar subjects. This significant effect is not surprising or particularly interesting.

There are several possible explanations for the non-significant results. Overall, a better methodology could have helped produce better results. The credibility manipulation check shows that there is not a significant difference between the perceived credibility level of TMZ and CNN. One way to improve this in future experiments is to use an even less credible source than TMZ. Additionally, the difference in credibility may have been less apparent because the message was about a celebrity. While in regards to politics or world issues TMZ may be viewed as a less credible, more rumor-based source than CNN, TMZ is a celebrity-focused website. And with its recent reporting of misinformation regarding the Boston Bombings, CNN showed that it is also vulnerable to be viewed as having low credibility. In the future it may be more interesting, and relevant to observe CNN or another news source as having high credibility and a random person on Twitter as having low credibility. In the future it may also be more useful to test messages about brands in order to have more specific marketing implications for the study. Another sign that the study may have benefited from a better methodology is that there was a small correlation and non-significant effect between users that have a twitter account and likeliness to share message (correlation= .004). Nearly 75% of survey respondents owned a Twitter account, but this had absolutely no effect on respondent's willingness to share the message. Another issue that arose during this study is that the morning of data collection, the negative message actually became a reality. Kevin Hart was actually arrested, and though it is unknown how many respondents knew of this information, it could have played a factor in the results. There could have also been certain cultural or social effects such as how people view comedians in general that may have introduced some bias in our results.

Upon having an improved methodology, this study could have several managerial and theoretical implications. This study could contribute to the theory on credibility/trust from online information sources and help identify mechanisms that cause the diffusion of false messages. This research could also provide information pertinent to managers and news organizations in controlling crisis communications. Just a few weeks ago CNN prematurely reported that one of the Boston Marathon bombers had been arrested, days before it actually happened. This situation presented a positive message seeming to be reported from a highly credible source. The message was retweeted and spread rapidly across social networks. The message began to take on its own truth, even though it was false. It would be beneficial to learn about the impact of such social influence and network effects in an online environment such as Twitter.

Future Methods

To further study this theoretical model, I would like to examine the diffusion of rumors surrounding a future Apple product announcement. Oftentimes, Apple product announcements are anticipated by the media and users alike. For months ahead of the official announcement, members of society speculate on the new updates and products that will be featured, but much information that circulates is unverified and merely just rumors. Sometimes these rumors are positive, hinting at new cutting edge features such as a retina display or sometimes they are negative, for example refuting claims that there would be a redesign of the Apple iPhone. Using the Twitter data collection application JAGS, 3000 tweets from each day in the month prior to a recent Apple announcement will be archived into a study dataset. The JAGS application can collect a sample of tweets in a date range that feature a user-selected hashtag or topic such as "Barack Obama" or "#Apple. For the purposes of this study we center on the hashtag "#AppleAnnouncement". By using just #Apple in the application, tweets that do not involve rumors about the announcement as well as tweets about the fruit could end up in the dataset. In addition to outputting a spreadsheet featuring the actual tweets, the application provides data on the number of times a message is retweeted, the users that tweet the most using that hashtag, as well as the users and tweets that are retweeted (shared) the most. The number of retweets of a particular message in this study would be used as a measurement for rebroadcasting behavior

To measure the valence of each tweet, sentiment analysis software, LIWC, would be used. Sentiment analysis is a knowledge discovery technique that aims at finding hidden patterns in tweets. It involves using natural language processing applications that use text mining to identify text sentiment polarity, typically as positive, negative, or neutral. To determine the polarity of the sentiment in a tweet, the text is compared to the sentiment scores of words in a pre-defined dictionary or lexicon. Recent studies have included the Hu and Liu (2004) lexicon, which includes around 6800 words (2006 positive words and 4783 negative words). Each word in the dictionary is assigned a positive, negative, and neutral score. For instance, a negative word might have a sentiment score of negative 0.375, positive 0.125 and objective 0.5.

To measure source credibility evaluators from Mechanical Turk would be asked to assess the credibility of 10 tweets, which are from the dataset. In total each tweet would need to be evaluated at least five times, and an average credibility score would be calculated.
Credibility would be assessed using the McCroskey & Teven (1999) measure which asks questions about the source of the message based on the constructs of competence, goodwill, and trustworthiness. Each construct is measured with six semantic differential type items, anchored with two antonyms (i.e., moral–immoral) and including a seven point response scale ranging from 1 to 7.

Theoretical Contributions and Managerial Implications

The findings of these studies can make several contributions to the information diffusion and marketing literature, and concurrently offer insight that would be beneficial to firms and brands. Theoretically, the conclusions of this study could extend rumor theory by providing depth to the literature regarding rumor rebroadcasting and dissemination. This article considers new qualifiers of content (credibility and valence) that influence rumor dissemination.
Additionally this study could contribute to the literature on influentials and opinion leaders, by

providing context to the influence struggle between mainstream media and influential individuals.

Solving these research questions could have many managerial implications as well. First, it is important for firms to understand how much control they have over the messaging about their brand in online environments. If consumers are more likely to believe messages from other consumers, then maybe firms should focus on disseminating their messaging through consumers, and exploiting positive co-creation effects. Firms may consider distributing their messages through influencers, instead of releasing press releases to news outlets to gain a more effective response. Also I think this research could help firms better understand communication amongst consumers about brands in online environments.

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Exhibit 1: Sample Tweet Shown To Respondents (Low Credibility/Negative)

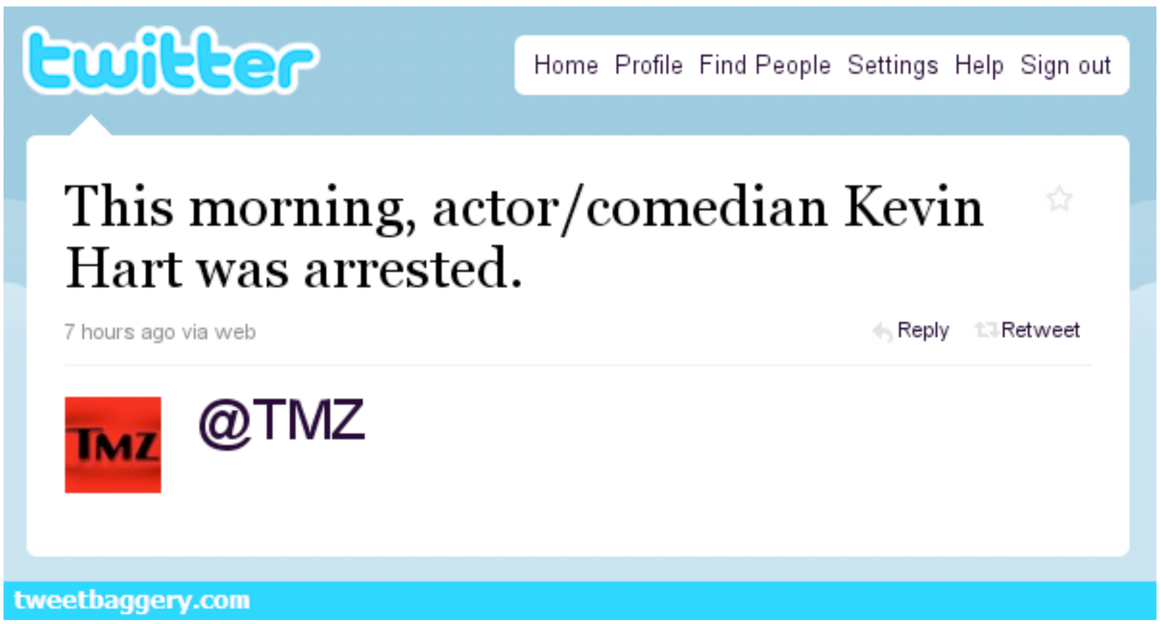

Exhibit 2: Manipulation Check

Report

This is a very positive message.

neg	Mean	N	Std. Deviation
0	5.61	64	1.063
1	2.92	61	1.509
Total	4.30	125	1.871

Report

AvgCredibilityScore

cred	Mean	N	Std. Deviation
0	5.2581	62	1.12166
1	4.9325	63	1.16242
Total	5.0940	125	1.14945

Exhibit 3

Pairwise Comparisons

Dependent Variable: I believe that this message is true.

(I) neg	(J) neg	Mean Difference (I-J)	Std. Error	Sig.[b]	95% Confidence Interval for Difference[b]	
					Lower Bound	Upper Bound
0	1	.756*	.215	.001	.332	1.181
1	0	-.756*	.215	.001	-1.181	-.332

Based on estimated marginal means

*. The mean difference is significant at the .050 level.

b. Adjustment for multiple comparisons: Least Significant Difference (equivalent to no adjustments).

Exhibit 4

Pairwise Comparisons

Dependent Variable: How likely are you to ReTweet (post) this message and share it with friends?

(I) cred	(J) cred	Mean Difference (I-J)	Std. Error	Sig.[a]	95% Confidence Interval for Difference[a]	
					Lower Bound	Upper Bound
0	1	-.034	.353	.924	-.732	.665
1	0	.034	.353	.924	-.665	.732

Based on estimated marginal means

a. Adjustment for multiple comparisons: Least Significant Difference (equivalent to no adjustments).

Exhibit 5

Pairwise Comparisons

Dependent Variable: How likely are you to ReTweet (post) this message and share it with friends?

neg	(I) cred	(J) cred	Mean Difference (I-J)	Std. Error	Sig.[a]	95% Confidence Interval for Difference[a]	
						Lower Bound	Upper Bound
0	0	1	-.558	.493	.260	-1.535	.418
	1	0	.558	.493	.260	-.418	1.535
1	0	1	.491	.505	.333	-.508	1.490
	1	0	-.491	.505	.333	-1.490	.508

Based on estimated marginal means

a. Adjustment for multiple comparisons: Least Significant Difference (equivalent to no adjustments).

Exhibit 6

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	2.792	.390		7.160	.000
	cred	.558	.493	.147	1.132	.260
	neg	.656	.498	.173	1.317	.190
	credneg	-1.049	.706	-.214	-1.487	.140

a. Dependent Variable: How likely are you to ReTweet (post) this message and share it with friends?

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	1.371	.483		2.839	.005
	cred	.454	.459	.120	.989	.325
	neg	.661	.463	.174	1.426	.156
	credneg	-.814	.658	-.166	-1.236	.219
	How familiar are you with Kevin Hart?	.379	.085	.376	4.453	.000

a. Dependent Variable: How likely are you to ReTweet (post) this message and share it with friends?