Linguistic Predictors of Rumor Veracity on the Internet

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***Abstract*—This paper attempts to investigate the role of language in predicting the veracity of rumors on the Internet. Specifically, it seeks to examine rumor veracity as a function of six groups of linguistic predictors. These include rumors' (1) comprehensibility, (2) sentiment, (3) time-orientation, (4) quantitative details, (5) writing style, and (6) topic. A dataset of 2,391 rumors, about 20% of which were true and the rest false, drawn from the rumor-verification website Snopes.com was used for investigation. The operationalized measures of the linguistic predictors were calculated for all rumors using the Linguistic Inquiry and Word Count (LIWC) tool. Binomial logistic regression was used for data analysis. The model performed generally well. The results specifically indicated that rumor veracity could be predicated by comprehensibility, time-orientation, writing style and topic of rumors.**

***Index Terms*—Online rumors, veracity, authenticity, trust, virality, linguistic analysis**

I. Introduction

THE Internet has now become the most convenient avenue to seek real-time information of all sorts ranging from everyday topics such as fashion and leisure to controversial ones such as politics and religion. Whenever individuals develop any information need, they tend to go online. Some users look for information using search engines, while others are often inclined to seek help from online communities through various social media applications.

Despite the convenience of the Internet as an information-seeking avenue, it needs to be taken with a grain of salt. Given the lack of rigorous quality control, the Internet often plays the role of what is known as a rumor mill [1]. Rumors refer to unverified information lacking a secured standard of evidence during circulation [2].

The Internet is a repository of both sound information as well as rumors. When users look for information, they might end up receiving rumors in their search results. It is quite possible for some of these rumors to subsequently emerge as being bogus. However, it is almost impossible for users to predict the veracity of rumors when the entries are being propagated online [3].

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The nature of rumors, and the problems posed by them have long been studied widely by scholars in the psychology discipline (e.g., [4]-[7]). Increasingly, the prevalence of rumors on the Internet is attracting attention from computer science and information systems scholars (e.g., [1], [2], [8], [9]). In particular, a nascent area of research seeks to examine the linguistic properties of the content of rumors. For example, [10] examined a dataset of the microblogging platform Twitter for misleading political rumors using Twitter-specific content features such as hashtags and mentions. Studies such as [11] likened the task of automated detection of online rumors to traditional natural language processing tasks, and in particular, to sentiment analysis. Furthermore, [12] conducted a text analysis of rumors by categorizing their contents into psychologically meaningful word categories. More recently, [2] found that rumors that are short and contain numbers are more likely to be true than those that are long and do not contain any quantitative details. Despite these works, the extent to which language used in rumors could offer hint about their veracity remains unclear.

Therefore, this paper attempts to investigate the role of language in predicting the veracity of rumors. Specifically, it seeks to examine rumor veracity as a function of six groups of linguistic predictors. These include rumors' (1) comprehensibility, (2) sentiment, (3) time-orientation, (4) quantitative details, (5) writing style, and (6) topic. Comprehensibility refers to the extent to which rumors are easy to understand. Sentiment is a measure of the use of affect in rumors. Time-orientation refers to the relative dominance of tenses in rumors. Quantitative details indicate the presence of statistics in rumors. Writing style is a measure of the ways words are used in rumors. Topic refers to the genre of rumors. The findings of the investigation could offer insights on discerning veracity of information on the Internet based on linguistic properties.

The remainder of this paper is organized as follows. The next section reviews related works. This is followed by the methods of data collection, measurement and analysis. The results are presented next. Thereafter, the findings gleaned from the results are discussed. The paper concludes by highlighting its implications and limitations.

II. Literature Review

Spread of rumors is a social phenomenon that has been running "*through the whole evolutionary history of mankind*" [13: p. 2444]. The advent of the Internet further serves as a fillip to this social phenomenon. This is because the speed of online information flow is generally much faster than it is in an offline setting. In consequence, information from the Internet—regardless of its veracity—generally reaches individuals earlier than from official authorities. Additionally, information received early is generally trusted by individuals due to what is known as primacy [14]. Even bogus rumors on the Internet thus stand a good chance to be widely trusted.

Therefore, it could be a timely research endeavor to investigate if the veracity of rumors could be predicted beforehand when they are in circulation. In this vein, a nascent area of research compares rumormongering to deceptive communication [2], [15]. Given that language has been extensively documented as a predictor of deception in both offline [16]-[18] and online [19]-[21] communication settings, it could also offer telltale signs insofar as rumor veracity is concerned. Taking the cue from such studies, this paper argues that there could be at least six groups of linguistic predictors to help ascertain rumor veracity. These include rumors' (1) comprehensibility, (2) sentiment, (3) time-orientation, (4) quantitative details, (5) writing style, and (6) topic.

Comprehensibility refers to the extent to which rumors are easy to understand. Succinct rumors containing short words generally have a good chance to permeate widely [7]. This is because the prospect of a rumor spreading through the community is generally constrained by the limitations of human memory. It is unlikely for a rumor to shape public opinion if it is too verbose, and its constituent words too lengthy [22]. Additionally, affirmative rumors could be easier to comprehend than those that use negations (e.g., not, never) [19]. It could be interesting to study if these dimensions of information comprehensibility are able to predict veracity of rumors.

Sentiment refers to the use of positive and/or negative affect in rumors. Rumors have different levels of outcome-relevant involvement. Rumors with low outcome-relevant involvement bear little consequences, whereas those on the higher end of the spectrum intricately influence individuals. This is because such rumors almost invariably connote either positive or negative emotions. In this vein, some studies found negative rumors to outnumber positive ones [23]. Others found that false rumors seldom contain positive emotion words [12]. However, variations in sentiment across true and false rumors largely remain unknown. Additionally, even though anxiety constitutes a key aspect of rumors [24], it is unclear if the presence of anxiety-related words (e.g., worry, nervous) in rumors help predict their veracity.

Time-orientation refers to the relative dominance of various tenses in rumors. Individuals' perception of time as a predictor of behavior has received much attention from economists, marketers and psychologists [25], [26]. However, time-orientation of rumors has hardly been empirically investigated hitherto. The veracity of rumors, which are known to spread as a result of individuals' attempt of sense-making amidst uncertainty [27], could be a function of the time-orientation indicated in rumors. Unlike rumors with a temporal focus on the future, those related to past or present could be supported with elements of empirical evidence, thereby making them more likely to emerge as being true.

Quantitative details refers to the presence of statistics in rumors in the form of numerals (e.g., 2, 100), numbers (e.g., second, hundred), or quantifiers (e.g., few, much). False rumors are likely to contain less specific information than true ones [28], [29]. This implies that rumors with specific quantitative details could be true. After all, it would be almost impossible to include numerical figures about events that are non-existent and hypothetical. In fact, studies such as [2] empirically showed that health rumors with quantitative details were likely to be true. Nonetheless, it is worthwhile to test if such a finding could be replicated for rumors of all topics in general.

Writing style refers to the ways words are used in rumors to express ideas. False rumors could be more vague and ambiguous vis-à-vis true ones [2]. Therefore, the former could be rich in discrepancy words (e.g., could, would), tentative words (e.g., guess, perhaps), filler words (e.g., blah, I mean), and punctuations. In some extreme cases, false rumors could even express offensiveness through the use of swear words (e.g., damn, piss) in order to draw attention [30]. On the other hand, true rumors could be rich in exclusion words (e.g., but, without) that generally enhance level of specificity in texts [31], [32].

Topic refers to the genre of rumors. Users seek information on various topics on the Internet. Some topics are related to personal concerns such as home, leisure, work, money and achievement. Others such as death and health not only pertain to personal well-being but also bear elements of surprise. Users also search for information on controversial topics such as religion and sex. Rumors could be prevalent on each of these topics. For example, corporate rumors related to workplaces [33], and health rumors [2], [6] have become commonplace. Controversial rumors on religion [34] and sex [35] are also quite prevalent. However, it is currently unclear if rumors' topics help predict their veracity. For the purpose of this paper, topics of rumors were ascertained through the use of words related to home (e.g., apartment, kitchen), leisure (e.g., cook, movie), work (e.g., job, designation), money (e.g., cash, owe), achievement (e.g., earn, hero), death (e.g., kill, coffin), health (e.g., clinic, pill), religion (e.g., church, mosque), and sex (e.g., horny, love) [31], [36].

III. Methods

A. Data Collection

Given that this paper seeks to investigate rumor veracity, it was necessary to obtain rumors that are known to be either true or false. This is why data were collected from Snopes.com, a popular rumor-verification website that confirms or debunks the veracity of latest rumors on the Internet. Whenever users encounter any rumors on the Internet, they can submit the entries to Snopes.com. The veracity of the rumors is investigated. When definitive evidence is obtained, rumors are labelled as either true or false on the website. Otherwise, they are indicated as undetermined. This functionality makes the platform particularly appropriate for data collection in this paper.

Additionally, Snopes.com is also one of the most popular

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websites for verification of rumors. It is frequented daily by some 300,000 visitors [37], with about 1.70 page views for each. Almost 80% of the visitors are from the United States [38]. Snopes.com has also set up its Facebook channel (www.facebook.com/snopes) in which it publishes links to the latest rumors. The Facebook page of Snopes.com currently has about 246,130 fans.

For the purpose of this paper, a total of 3,938 rumors were retrieved from Snopes.com. From this initial pool, only those rumors whose veracity was indicated by Snopes.com as either true or false were retained. This yielded a dataset of 2,391 rumors for analysis. Of these, only 480 rumors (about 20%) were true while the rest were false. Based on the proportions, rumors on the Internet appear more likely to emerge as being false than true, all other things being equal. This further reinforces the need to study the possible predictors of rumor veracity on the Internet.

B. Measurement and Analysis

The linguistic predictors were measured using the Linguistic Inquiry and Word Count (LIWC2007) tool [36]. Given a rumor, its comprehensibility was measured as length in terms of number of words, fraction of words longer than six characters, and the use of negations (3 measures). Its sentiment was computed as the fraction of positive emotion words, negative emotion words, and anxiety words (3 measures). Its time-orientation was measured as the fraction of words in past, present, and future tenses (3 measures). Quantitative details in the rumor was calculated as the use of numerals, numbers and quantifiers (3 measures). Its writing style was measured as the fraction of discrepancy words, tentative words, filler words, punctuations, swear words, and exclusion words (6 measures). To ascertain the rumor’s topic, the fraction of words related to home, leisure, work, money, achievement, death, health, religion and sex were utilized (9 measures). These nine were chosen because information on these topics are widely available on the Internet. Moreover, the lexicon of LIWC has dedicated corpora for measuring these topical word categories.

Taken together, this paper used a total of 27 variables to quantify the linguistic properties of rumors. Analysis was done using binomial logistic regression. The 27 linguistic measures were taken as the independent variables. The dependent variable included rumor veracity (1 = true rumors, 0 = false rumors). Prior to analysis, the pair-wise correlations among the independent variables were checked. Given that all pairs of independent variables had correlations much lower than 0.80, multicollinearity was not a problem in the analysis [39].

IV. RESULTS

Table I summarizes the nature of the dataset in terms of the linguistic properties while Table II presents the logistic regression results highlighting only the statistically significant independent variables (in terms of odds ratio, which is denoted as Exp(β)) for predicting rumor veracity. The model performed generally well in predicting rumor veracity (χ^2 = 163.24, df = 27, $p < 0.001$, deviance = 2234.67, Nagelkerke pseudo-R^2 = 10.40%). A non-significant result for Hosmer-Lemeshow goodness-of-fit test (χ^2 = 5.99, df = 8, $p < 0.65$) further confirmed that the model fitted adequately well with the data.

With respect to comprehensibility, the use of negations (Exp(β) = 1.11, p = 0.01) was positively related to rumor veracity. The greater the use of negations in a rumor, the higher was its likelihood to turn out to be true. In other words, rumors phrased negatively were more likely to be true compared with affirmative ones even though the latter is generally easier to comprehend than the former.

With respect to time-orientation, past tense (Exp(β) = 1.03, p = 0.04) was positively related to rumor veracity. However, both present (Exp(β) = 0.89, $p < 0.001$) and future (Exp(β) = 0.82, $p < 0.001$) tenses had negative association with the dependent variable. This indicates that rumors rich in past tense but scanty in terms of present and future tenses were likely to be true.

With respect to writing style, the use of discrepancy words (Exp(β) = 1.17, $p < 0.001$) and swear words (Exp(β) = 1.17, p = 0.02) was positively related to rumor veracity. However, the use of exclusion words (Exp(β) = 0.88, p = 0.01) had negative association with the dependent variable. Thus, rumors rich in discrepancy and swear words but scanty in terms of exclusion words were likely to be true.

With respect to topic, the use of home (Exp(β) = 1.05, p = 0.04) and leisure (Exp(β) = 1.02, p = 0.03) related words was positively related to rumor veracity. However, the use of religion (Exp(β) = 0.95, p = 0.03) and sex (Exp(β) = 0.91, p = 0.01) related words had negative association with the dependent variable. Stated otherwise, rumors that dealt with non-contentious topics such as home and leisure were likely to be true. On the other hand, rumors on controversial topics such as religion and sex were likely to be false. Interestingly, the use of sentiment and quantitative details could not help predict rumor veracity.

TABLE I
DESCRIPTIVE STATISTICS OF THE LINGUISTIC PREDICTORS

Ling. predictors	Measures	Mean ± SD	Min	Max
Comprehensibility	Length	16.87 ± 26.66	4	808
	SixChar	27.71 ± 11.74	0	83.33
	Negation	0.32 ± 1.52	0	27.27
Sentiment	PosEmotion	1.64 ± 3.71	0	44.44
	NegEmotion	2.18 ± 4.23	0	37.50
	Anxiety	0.22 ± 1.24	0	17.65
Time-orientation	Past	2.80 ± 4.22	0	25.00
	Present	3.57 ± 5.32	0	60.00
	Future	0.54 ± 1.95	0	35.71
Quantitative	Numerals	1.35 ± 3.25	0	30.00
	Numbers	0.95 ± 2.98	0	37.50
	Quantifiers	1.05 ± 2.60	0	18.75
Writing style	Discrepancy	0.30 ± 1.42	0	15.38
	Tentative	0.59 ± 2.04	0	28.57
	Filler	0.07 ± 0.91	0	21.43
	Punctuation	15.81 ± 11.46	0	85.71
	Swear	0.03 ± 0.73	0	30.00
	Exclusion	0.47 ± 1.98	0	33.33
Topic	Home	0.49 ± 1.97	0	21.43
	Leisure	3.68 ± 5.69	0	50.00
	Work	3.29 ± 5.49	0	44.44
	Money	1.40 ± 3.75	0	37.50
	Achievement	2.04 ± 4.22	0	44.44
	Death	1.14 ± 3.21	0	33.33
	Health	0.96 ± 3.04	0	37.50
	Religion	0.78 ± 2.99	0	33.33
	Sex	0.43 ± 1.98	0	30.00

TABLE II
LOGISTIC REGRESSION RESULTS

Ling. predictors	Measures	Exp(β)	Sig. level (p)
Comprehensibility	Negation	1.11	0.01
Time-orientation	Past	1.03	0.04
	Present	0.89	< 0.001
	Future	0.82	< 0.001
Writing style	Discrepancy	1.17	< 0.001
	Swear	1.17	0.02
	Exclusion	0.88	0.01
Topic	Home	1.05	0.04
	Leisure	1.02	0.03
	Religion	0.95	0.03
	Sex	0.91	0.01

V. DISCUSSION AND CONCLUSION

The results of this paper indicate that some linguistic properties of rumors offer telltale signs to predict their veracity. In particular, rumor veracity were predicated by four groups of linguistic predictors: (1) comprehensibility, (2) time-orientation, (3) writing style, and (4) topic.

With respect to comprehensibility, negatively-phrased rumors were more likely to emerge as being true compared with affirmative rumors. Prior research suggests that affirmative sentences can be processed more easily and quickly than those that include negations [40]. This is because it is always easier to comprehend what is done vis-à-vis what is not done [19]. Ironically, it seems that negatively-phrased rumors were likely to emerge as being true notwithstanding the difficulty in terms of their comprehensibility.

With respect to time-orientation, rumors rich in past tense but scanty in terms of present and future tenses were likely to be true. To the best of the authors' knowledge, this paper makes the first attempt to examine the relative use of tenses in rumors. The investigation was motivated by the premise that rumors propagate due to individuals' sense-making behavior [27], which in turn could be shaped in part by temporal focus [25], [26]. Rumors rich in past tense (e.g., historical rumors) were more likely to be true perhaps because they had the possibility of being supported by factual or empirical evidence. Obtaining evidence for rumors that deal with the present or the future is conceivably difficult.

With respect to writing style, rumors rich in discrepancy and swear words but scanty in terms of exclusion words were likely to be true. There is evidence that discrepancy words are mostly used by individuals in a troubled state of mind [41], while swear words are often used to draw attention [30]. However, it is currently unclear how those experiencing conflict might create true rumors in order to seek attention from others. Moreover, even though prior studies expect genuine information to be richer in exclusion words than deceptive content [31], [32], the converse is found to be true for rumors. Such counter-intuitive findings highlight the complexity involved in the spread of rumors. More research is needed to identify the underlying reasons and mechanisms that could explain these findings.

With respect to topic, rumors that used words on non-contentious topics such as home and leisure were likely to be true. On the other hand, rumors that were rich in words on controversial topics such as religion and sex were likely to be false. Given that rumors are part of our everyday life [1], [2], [4], [5], [7], [13], [34], it is encouraging to find that those dealing with non-contentious and innocuous topics were likely to turn out true. However, controversial rumors were likely to emerge as being false. This suggests that users should not jump to conclusions soon after coming across controversial news on the Internet. Bogus controversial information could be spread by rumormongers perhaps only to destroy loyalties and promote aggression [7].

Interestingly, it was found that the use of sentiment and quantitative details in rumors could not predict their veracity. This finding contradicts prior works such as [12], which found sentiments useful in predicting rumor veracity in Twitter, as well as those like [2], which deemed the use of quantitative details a crucial predictor of veracity for health rumors. These contradictory findings warrant further investigation into this research theme on rumor veracity.

The significance of this paper is two-fold. First, it extends the literature on rumors by examining their veracity as a function of linguistic predictors such as time-orientation and topic, which have hardly received much scholarly attention thus far. Additionally, on testing linguistic predictors such as comprehensibility, sentiment, writing style and topic, the paper gleans findings that somewhat contradict those obtained from previous studies [2], [12], [31]. By exposing the lack of consensus, this paper calls for more fine-grained scholarly investigation to shed greater light on veracity of rumors on the Internet.

Second, this paper serves to remind users that information obtained from the Internet should always be taken with a grain of salt due to the growing prevalence of bogus rumors [1], [34]. This is especially important because it is almost impossible to guess beforehand if a rumor will eventually turn out to be true or false. Therefore, this paper calls for careful attention and critical thinking on the part of users while seeking information—especially on controversial topics—from the Internet [9].

The findings of this paper should be viewed in light of two shortcomings that could be addressed in future works. First, the paper used linguistic measures that are available for calculation in LIWC2007. Even though the tool facilitates measuring a comprehensive set of word categories and is widely used in research [12], [14], it could be worthwhile to examine rumor veracity by casting a wider net of linguistic predictors that extend beyond a single tool. Additionally, LIWC analyzes texts lexically without parsing them for semantics. Therefore, the use of the tool prevented examining how the veracity of rumors differed across the use of figures of speech as well as rhetorical devices such as idioms, ironies, metonymies, sarcasms and synecdoches.

Second, even though this paper investigated the extent to which rumor veracity could be predicated by linguistic predictors, it failed to consider if the use of language could also offer hints about the virality of rumors. It could be interesting to examine the relative likelihood for true as well as false rumors to spread on the Internet as a function of their linguistic properties. Such studies are necessary to further extend the scholarly understanding on rumors on the Internet.

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