On the Credibility Perception of News on Twitter: Readers, Topics and Features*

Abstract: Searching for specific topics on Twitter, readers have to judge the credibility of tweets. In this paper, we examine the relationship between reader demographics, news attributes and tweet features with reader's credibility perception, and further examine the correlation among these factors. We found that reader's educational background and geo-location have significant correlation with their credibility perception, and furthermore the news attributes in tweets are also significantly correlated with reader's credibility perception. Despite differences in demographics, readers find features including the search topic keyword and the writing style of tweets most helpful in perceiving tweet credibility. While previous studies reported the use of specific features, our results showed that readers use combination of features to make decisions regarding tweet credibility. Comparing the credibility level predicted by an automatic prediction tool and that by reader's perception, we found that readers tend to be more trusting, possibly due to the limited explicit author information available on Twitter. Our study can help devise strategies to enhance the tweet credibility with readers and also help educate readers to be more cautious with information credibility on Twitter.

Keyword: Reader's demographics, credibility perception, news attributes, tweet features

1 Introduction

In the information seeking process, information can come from known and unknown sources. This information may come from books, newspapers, digital sources and even from another individual (McKenzie, 2003). Improvement in big data management allows users search and find the appropriate information they require, and optimize the resources for speedy search as surveyed by Siddiqa et al. (2016). Nowadays, the online social media also acts as an information source for news. For example, Twitter's trending topics are often found to be up to date with CNN news headlines (Kwak et al., 2010). Online social media users routinely encounter knowledge online and share that information with their friends and the public via their social network accounts (Caverlee et al., 2010).

The news information in social media, especially Twitter, is becoming an established feature for crisis news events. People living in the disaster or crisis area often check for information and updates regarding the crisis on Twitter (Thomson et al., 2012). Even emergency responders begin to incorporate social media sites into their communication strategies with the public (Hughes and Palen, 2012).

Twitter posts, or tweets, from reputable news agencies and trusted authors via known social links are generally trustworthy. However, when Twitter readers search for tweets regarding a particular topic, the returned messages require readers to determine which tweet is trustworthy by themselves. Therefore, in this paper, we focus on studying the credibility of information on Twitter. We adopted the notion of credibility by Tseng and Fogg (1999) – "credibility is the quality of being believed or accepted as true, real, or honest, whether it regards the information or the source". In this sense, we distinguish credibility from trust in this research.

There are several pieces of research regarding the automatic detection of tweet credibility using various features, especially in distinguishing the credibility for news tweets and rumour tweets (Castillo et al., 2011; Gupta et al., 2014; Gupta and Kumaraguru, 2012; Kang et al., 2012; ODonovan et al., 2012). These studies focus on building automatic credibility classifiers by machine learning. Research regarding features that influence reader's credibility perception of tweets are also found in the studies by (Kang et al., 2015; Morris et al., 2012; Shariff et al., 2014;

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Yang et al., 2013). More broadly, different types of features are also used for recommender systems (Rohani et al., 2014) and personality prediction (Golbeck et al., 2011) for online social networks. However, there are no studies on understanding Twitter reader's credibility perception based on the reader's demographics.

More broadly, there has been research on information crediblity for other online media. Research that studies reader credibility judgements on web blogs, Internet news media, and websites can be found in the studies by Fogg et al. (2001), Greer and Gosen (2002), Yang et al. (2013) and Yang (2007). Quantitative studies were conducted on limited groups of participants to study specific factors that influenced reader's credibility judgements on cross platform (Kang et al., 2015). Since these user studies focused on specific factors, the subjects for reader's credibility assessment were controlled and limited.

We have found that there is a gap in understanding the relationship between Twitter reader's background and their credibility judgements of news tweets. We aim to understand the factors influencing reader's credibility judgement of tweets, especially when tweets are from authors outside of the reader's trust network (the follower-followee relationship), such as tweets retrieved from a query request. Similar to previous studies, we design a user study of 1,510 tweets about 15 search topics that are judged by 754 participants. We will focus only on tweet content features as presented by the Twitter platform and available directly to readers at a first glance as describe by the previous study (Shariff, Sanderson, and Zhang 2016).

We will explore the correlation between reader's demographic attributes, news topics and features with reader's credibility judgements. The correlation analysis is further examined among these factors. We also analyse the association between reader's demographics and news attributes towards the perception of tweet's credibility level. We hypothesise that reader's credibility perception of different news attributes does have relations with other factors. The contributions in this paper are as follows:

- We find that the information credibility level for tweets by reader's perception is different from the predicted credibility level by the automatic prediction tool. We further find that the reason for the difference is that humans are more trusting to the information shared on Twitter.
- Little attention has been given in previous studies regarding the relationship among factors that influence credibility perception of tweets, especially concerning reader's demographic profiles. We analyse the correlation and prove in Sections 4 and 5 that reader's demographics, news attributes and tweet features do have significant relationship with reader's credibility perception. Specific news attributes are also shown to associate with reader's demographics in regards to their perceived credibility level of tweets.

2 Related work

Related work comes from three areas: credibility and trust in general, user perception of credibility in online media and information credibility on Twitter.

2.1 Credibility and trust

Credibility and trust are closely related. Mayer, Davis, and Schoorman (1995) defined trust as *"willingness of a party to be vulnerable to the actions of another party based on the expectation that the other will perform a particular action important to the trustor, irrespective of the ability to monitor or control that other party"*. Wang and Emurian (2005) further listed the four characteristics of trust widely accepted by researchers: trustor and trustee (the relationship between two parties), vulnerability (involve uncertainty and risk), produced actions (transactions or activities between the two parties) and subjective matter (behaviour or attitude of the two parties regarding the transaction that occurred). Based on the two definitions, we can view trust as the interpersonal relationship between a trustor (the person who trusts) and a trustee (the person being trusted).

Tseng and Fogg (1999) describe credibility and trust of the computing technology. In their work, trust is about the dependability and reliability towards an object or person in a positive way, while credibility is regarding the believability or trustworthiness of the information's quality or the quality of the source from where the information comes. Tseng and Fogg indicate that there are two key elements in the measurement of credibility: trustworthiness and expertise. Their definition of credibility concur with the findings by Hovland and Weiss (1951) that a piece of information coming from an expert receives higher credibility perception than the information that comes from a questionable source. Rieh and Hilligoss (2008) added that personal characteristics also play an important role towards the measurement of credibility. In their interviews with college students, Rieh and Hilligoss discover a person's experience and similar social connections does influence the credibility judgement of information, online or offline. Here, we can see that trust is deeper than credibility and only happens after credibility, indicating the importance of credibility perception.

2.2 User credibility perception in online media

There has been extensive work regarding credibility perception of online digital media on the Internet such as websites, blogs and social networks. The credibility of information on the Internet is perceived higher by experienced and savvy users rather than less experienced users. Youngsters are also an important target group in need of awareness and knowledge in identifying credible online information as they are more vulnerable in deciding what is the truth (Rahim et al., 2015). The freedom users have in choosing the information from the source they deem credible based on their experience and verification contribute to the high credibility rating of the Internet (Flanagin and Metzger, 2000). In the work by Fogg et al. (2001), participants from Finland and US completed the survey regarding the credibility perception of websites. The demographic profiles are shown to correlate with the credibility ratings of websites. They discovered that website credibility elements such as interface, expertise and security are influenced by user's demographic attributes.

Another study found that the manipulation level of news photos influenced credibility perception of news media (Greer and Gosen, 2002). The study showed that one's demographics influenced his/her perception of media credibility. Users find highly altered photograph published online to be less credible. A Taiwanese-based study of reader's credibility perception regarding news-related blogs found that the belief factor can predict user's perceived credibility (Yang, 2007). They also found that reader's motivation in using news-related blogs as a news source influenced their credibility perception. Demographic variables were also shown to affect credibility. In another study by Kang, Höllerer, and O'Donovan (2015), demographic attributes are also found to correlate with visual features of microblog posts that are information credibility factors, especially for young people.

2.3 Information credibility on Twitter

On the Twitter platform, most studies on credibility focus on credibility prediction and tweet features affecting credibility perception. Limited research studies credibility perceptions in regard to readers. A class of existing studies focused on tweet credibility prediction by supervised learning using features from tweet contents, the tweet author's social network, and the source of retweets. Prediction models trained from human annotated credibility ratings are used to predict the credibility of unseen tweets (Castillo et al., 2011). The tweet credibility prediction model presented in the study by Gupta and Kumaraguru (2012) were used to rank the news event tweets by credibility using content-based features such as the number of unique characters in the tweet, and user-based features like the length of the author's username. TweetCred (Gupta et al., 2014) is a public Tweet credibility prediction tool based on the study by Gupta and Kumaraguru (2012). Both works used a current trending topics dataset. Other studies focused on the utility of individual features for automatically predicting credibility, such as the work by ODonovan et al. (2012) regarding topic-specific tweet collections, and on the credibility verification of tweets for journalists based on the author's influence, the media and information quality and the geolocation of the author as an eyewitness for the news event (Schifferes et al., 2014).

Another class of research examined the features influencing reader's credibility perception of tweets. Examining only certain tweet features, Morris et al. (2012) studied just under 300 readers from the US. The authors identified that a tweet written by authors with a topically related display name influenced reader credibility perception. Yang et al. (2013) conducted similar research, comparing readers from China and the US, and they found that different cultural background affect the credibility perception of tweets differently, in terms of what and how features were used.

The differences in tweet credibility perception for different topics were also reported in the study by Shariff, Zhang, and Sanderson (2014). The study found eight tweet-content features readers use when judging the credibility level of tweets. The reputation of the source or tweet author is also part of the key elements to determine the credibility level of information shared on Twitter by users (Westerman, Spence, and Van Der Heide 2012). Note that none of these existing works studied the demographics of readers and their tweet credibility perception.

Sundar (1999) describes that one's perception of online news stories depends on four factors: credibility, liking, representative and quality. Therefore, the evaluation we are looking for in this study is the reader's credibility perception of news information, particularly when readers search the online social network for news stories and read the news stories by authors not within their trust social network (Hu et al., 2012; Petrovic et al., 2013). Husin, Thom, and Zhang (2013) described that social network users access news agency websites for further information by the hyperlink embedded in the news story posts, which is a verification act as reported in Rieh and Hilligoss (2008).

3 Methodology

In this section, we describe our methodology for data collection and analysis. Specifically, our methodology comprises the following steps:

- Step 1: Collection of tweet messages.
- Step 2: Collection of credibility ratings for tweet messages by automatic prediction.
- Step 3: Collection of credibility ratings by reader's credibility perception.
- Step 4: Questionnaire design for collecting reader's demographic data.
- Step 5: Chi-square analysis design for correlation among user demographics and credibility ratings.
- Step 6: Cohen's Kappa analysis design for contrasting credibility ratings by human perception and automatic prediction.
- Step 7: Association analysis design for user demographics, news attributes, tweet features and credibility ratings.

The steps are next described in details in Sections 3.1—3.7.

3.1 Tweet message collection

We compiled tweets from three news categories: breaking news, political news, and natural disaster news, the same categories used in past studies (Morris et al., 2012; Yang et al., 2013). Each news category consists of five world news topics reported by news agencies including BBC, Reuters and CNN from 2011 until May 2014. We made sure that the news topics were evenly divided between trending and not trending topics. Trends were determined from the trending list on Twitter and “What the Trend”, a Twitter page (@whatthetrend) which is part of the HootSuite Media that lists Twitter's trending topics; helps define and understand trending topics on Twitter.

The tweets were manually examined to ensure they were topic related tweets and randomly picked from the topic search result by Twitter. The method of search using keywords for relevant online documents has been conducted by previous studies (Kang et al., 2012; Rahim et al., 2015; Shariff et al., 2016). In the news tweet collection, two writing styles of tweets are included - a style expressing author’s opinion or emotion towards the topic and another just reporting factual information. The writing styles were used after results from a pilot user study indicated that readers also find tweets expressing an author’s feelings regarding a topic as credible.

3.2 TweetCred credibility rating

We also collect real-time credibility rating of the same tweets shown to readers using an automatic credibility prediction tool TweetCred (Gupta et al., 2014). TweetCred is a Chrome extension application that gives a real-time credibility score about a tweet based on six types of features: meta-data, content-based simple lexical features, content-based linguistic features, author, external link URL’s reputation, and author network (Gupta et al. 2014). The credibility rating predicted by TweetCred is displayed next to the author’s display name or beside the date. Fig. 1 shows the credibility rating of 6 out of 7 predicted by TweetCred, where Figure 1(a) is a snapshot for Twitter search and Figure 1(b) is the larger view of the tweet when users click on the tweet post.

3.3 Data collection

Since we are aiming for broad participation in our study, a crowdsourcing platform was used to recruit participants. The use of crowdsourcing for annotating tweet credibility can be found in prior works (Castillo, Mendoza, and Poblete 2011; Gupta and Kumaraguru 2012; Kang, Höllerer, and O’Donovan 2015; Shariff, Zhang, and Sanderson 2014). Conducting online surveys on the crowdsourcing platform allows us to get a large number of international respondents within a short time and cost lower than the traditional survey (Mason and Suri, 2012). Furthermore, the nature of Twitter that allows anyone (both account and non-account holder) to search for tweet messages and view them makes it possible for us to conduct the survey on the crowdsourcing platform. Therefore, we designed the user study on the CrowdFlower (www.crowdflower.com) platform, one of the popular crowdsourcing platforms used by researchers (Peer et al., 2016).

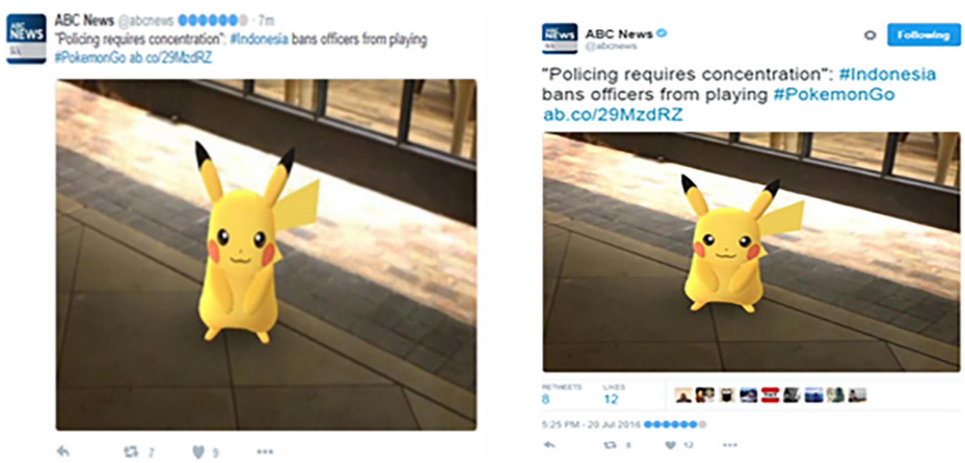
3.4 Questionnaire design

We divided the questionnaire into two parts. The first part of the questionnaire regards the basic demographic questions: gender, age, and education level. The country information is supplied to us by the CrowdFlower platform as it is part of the worker’s information upon registration. The workers are seen as tweet readers in this paper.

The second part of the questionnaire regards perception judgements of the credibility of news-related tweets. A number of pilot studies were run to determine the optimal number of tweet judgements readers were willing to make. Twelve judgements per reader were the number chosen empirically.

Readers were shown tweets as they would be shown in a Twitter search result page, retrieved in response to a search topic. Readers were also shown the topic and topic description. Without expanding the tweet to see any additional comments, the readers were asked to give their perceived credibility level of the tweet. Four levels are listed: very credible, somewhat credible, not credible, and cannot decide, which is based on the study by Castillo, Mendoza, and Poblete (2011) and Gupta and Kumaraguru (2012).

Upon judging, readers were asked to describe what feature/s of the tweet they use to make the judgement. We prompt the readers with a list of features reported in previous research by Castillo, Mendoza, and Poblete (2011) and Shariff, Zhang, and Sanderson (2014) if they answered 'very credible' and 'somewhat credible', as well as encouraging them to describe other features in the free text interface. For the negative answers 'not credible' and 'cannot decide', we ask the readers to describe the reason for their credibility judgements. The two different methods are chosen based on our pilot study where free text gives us more insight regarding the way readers make a negative credibility judgement.



(a) (b)

Fig. 1 The credibility rating for a tweet predicted by TweetCred

3.4.1 Quality control

As our credibility judgement design is different for the positive (very credible and somewhat credible) and negative (not credible and cannot decide) credibility levels, we analyses the collected judgements by readers to be sure that the judgements are not biased towards the positive and that negative judgements are not opted out by the readers due to the free text design. Our analysis shows that a total of 227 readers have chosen at least one negative credibility level from the dozen random tweets shown to readers. The majority of workers chose from one to three negative credibility judgements. The readers that perceive tweets as 'not credible' and 'cannot decide' are seen to be reliable with their judgements since the negative credibility judgements are chosen no matter of the tweet display order. We also find that readers do not stop from rating negative credibility level of tweets after rating a tweet as either 'not credible' or 'cannot decide'.

To ensure the quality of answers by readers, a set of gold questions are shown to readers. Readers were required to answer the gold questions at a minimum of 80% qualifying level before they were allowed to progress. The gold questions were standard awareness questions, e.g. determining whether a topic and a tweet message were about the same news topic. The gold questions were not counted as part of the user study.

3.5 Chi-square Test of Independence

The Chi-square test of independence is used to establish if two categorical variables have significant correlation. The test calculated the difference between observed values and expected values. The cut-off acceptance for the relationship is based on the accepted probability level (p-value) of 0.05. The chi-square statistic test can be calculated as follows, where O_i and E_i are the observed value and expected value for cell i of the contingency table (McHugh, 2013):

$$\mathcal{X}^2 = \sum_{i=1} \frac{(O_i - E_i)^2}{E_i}$$

In this study, in addition to correlation analysis regarding individual demographic attributes and credibility judgements, we also aim to analyse how combinations of demographic attributes correlate with credibility judgements. Therefore, multi-way chi-square tests are also performed. Let $V_1, \ldots,$ and V_k be k binary variables, the contingency table to calculate the $\mathcal{X}^2$ for these k binary variables is $(V_1, \bar{V}_1) \times (V_2, \bar{V}_2) \times \ldots \times (V_k, \bar{V}_k)$. For example, when there are three binary variables A, B and C, to find out if variables A and B are correlated with variable C, the $\mathcal{X}^2$-statistic would be $\mathcal{X}^2(ABC) + \mathcal{X}^2(AB\bar{C})$ (Brin et al., 1997). Note that the chi-square statistic for binary variables is upward-closed, this means that the $\mathcal{X}^2$ value of ABC would always be greater than the $\mathcal{X}^2$ value of AB. Therefore, if AB is correlated, adding in variable C, ABC must also be correlated. Refer to the paper written by Brin, Motwani, and Silverstein (1997) for proof of the theorem.

In our problem setting, we apply the theorem to prevent false discoveries for multi-way chi-square analysis. Assuming that A and B are independent variables for demographic attributes and C is the dependent variable for credibility levels. If A and B are correlated, even if A, B, and C are correlated, we would not be able to tell if the association between credibility level C and the demographic attributes (A and B) is due to an actual effect or to the correlation between A and B. We first apply chi-square analysis between individual demographic attributes and the credibility judgements. If the result is insignificant, multi-way correlation analysis for combination of demographic attributes will be applied. To this end, the correlation for pairwise demographic attributes is first analysed. If the attributes are significantly correlated, we will not continue the $\mathcal{X}^2$ test between the pair and credibility judgements. We similarly analyse the correlation between demographic attributes and features readers use for credibility judgements. We also measure which cell in the contingency table influences the $\mathcal{X}^2$ value. The interest or dependence of a cell (c) is defined as $I(c) = O(c)/E(c)$. The further away the value is from 1, the higher influence it has on the $\mathcal{X}^2$ value. Positive dependence is when the interest value is greater than 1, and a negative dependence is those lower than 1 (Brin et al., 1997).

In this study the demographic data collected from the readers are used for chi-square analysis, as shown in Table 1. The reader's demographic data, except for gender, are also categorised in binary and categorical setting based on other research to examine any correlation of demographic attributes or combinations of demographic attributes with tweet credibility perception (Fogg et al., 2001; Greer and Gosen, 2002). The different ways of partitioning demographic data are as follows:

- Age: Binary {Young adult (≤39 years old), Old adult (≥40 years old)} and Categorical {Boomers (51-69 years old), Gen X (36-50 years old), Gen Y(21-35 years old), Gen Z (6-20 years old) (McCrindle et al., 2010)
- Education: Binary {Below university level, University level} and Categorical {School level, Some college, Undergraduate, Postgraduate}
- Location: Binary {Eastern hemisphere, Western hemisphere} and Categorical {Asia-Pacific, Americas, Europe, Africa}

We conduct the Chi-square correlation analysis for each single demographic attribute for all the different slicing with credibility judgements or features.

3.6 Cohen's Kappa

Cohen's Kappa statistical analysis is used to find the agreement between two independent observers' rating for the same set of things. If the two observers randomly assign their ratings, there are chances that their ratings would sometimes agree with one another. The Kappa's calculation is based on the difference between the observed agreement ratings compared to the expected agreement ratings by chance. The equation for Cohen's Kappa is shown below (Banerjee et al., 1999).

$$k = \frac{P_o - P_e}{1 - P_e}$$

Kappa's score is standardised to [-1...1], where 1 indicates perfect agreement, 0 indicates agreement by chance, and negative values indicate no agreement. Cohen's Kappa is used to determine the agreement level between the credibility rating predicted by TweetCred and reader's perceived credibility level by majority vote. TweetCred scores the credibility level of a tweet using a 7-scale rating. The 7-scale rating is further categorised into three credibility levels (the same as human judgements): 1 and 2 are not credible, 3 to 5 are somewhat credible, and 6 and 7 are very credible. Afterwards, the agreement matrix is built to perform the Cohen's Kappa analysis. The result from the statistical analysis is then compared to the Cohen's Kappa agreement interpretation range described by Viera and Garrett (2005) to identify the agreement level between the two.

3.7 Association rule mining

Association rule mining aims to extract interesting associations from among sets of items in transaction databases (Agrawal et al., 1993; Tan et al., 2005). Association rules are used in areas such as retail, marketing, inventory. An association rule is written as X→Y, where X and Y are sets of items, and X ∩ Y = ∅. X is called antecedent while Y is called consequent. The rule, X→Y, means X implies Y.

Two important measures for association rules are support and confidence. Users predefine thresholds (minimums) for support and confidence. The thresholds are meant to drop rules that are not so interesting or useful. The support of an association rule is the fraction of transactions containing items in X ∪ Y.

$$Support\ (X \rightarrow Y) = \frac{\#\ of\ transaction\ containing\ (X \cup Y)}{overall\ transaction\ (N)}$$

The confidence of an association rule is the fraction of transactions containing that also contain Y.

$$Confidence\ (X \rightarrow Y) = \frac{\#\ of\ transaction\ containing\ (X \cup Y)}{\#\ of\ transaction\ containing\ (X)}$$

Another metric proposed by (Brin et al., 1997) regarding identifying the interesting rules named lift is also used in this study. In general, lift is the ratio of the observed support of X ∪ Y to that expected if X and Y are independent:

$$Lift = \frac{support(X \cup Y)}{support(X) \times support(Y)}$$

A lift value greater than 1 implies that the degree of association between the antecedent and consequent item sets is higher than when the antecedent and consequent item sets are independent.

We administer the association rule mining in this study to find interesting rules that describe the relation between the reader's demographics and news attributes in terms of reader's perceived credibility level of news tweets. In this study, we apply the lift metric to determine interesting rules from association rule mining.

4 Results

A total of 10,571 credibility judgements for 1,510 news tweets were collected from the user study. Only 9,828 judgements from 819 crowdsource workers were accepted for this study because only these workers answered the demographic questions and completed all 12 judgements.

CrowdFlower workers who do not describe the features used for their credibility judgements or who gave nonsensical comments are ineligile as readers, and all their judgements were discarded. We also discarded judgements of two readers from Oceania continent, and three readers that did not have any education background, due to their low values undermine the required minimal expected frequency to apply $\mathcal{X}^2$ analysis. We were left with a final dataset for analysis from 754 readers with 9,048 judgements.

4.1 Overall demographics

Our final collection of data includes readers from 76 countries with the highest number of participants coming from India (15%). We then group the countries into continents due to the severe data sparsity at the country level. Out of 754 readers, the majority (69.0%, n=521) of readers were male, similar to prior work that uses crowdsource workers for user study (Kang et al., 2015). Most of the readers were in the age group of 20-29 years old (43.4%, n=327). In regard to reader's education background, the majority had a University degree (38.1%, n=287). Table 1 shows reader's demographic profiles.

Table 1 Demographic profiles distribution

Demographic	Value	#	%
Gender	Male	521	69.2
	Female	233	30.8
Age	16-19 years old	58	7.7
	20-29 years old	327	43.4
	30-39 years old	243	32.2
	40-49 years old	89	11.8
	50 years and older	37	4.9
Education	High school	127	16.8
	Technical training	58	7.7
	Diploma	81	10.7
	Bachelor's degree	287	38.1
	Master's degree	137	18.2
	Doctorate degree	14	1.9
	Professional certification	50	6.6
Location	Asia	275	36.5
	Europe	247	32.8
	South America	130	17.2
	North America	65	8.6
	Africa	37	4.9

4.2 News attributes

Other than the demographic profiles of Twitter readers, we also aim to establish whether the news attributes of tweets affect reader's credibility perception. Specifically, news attributes include the news type — breaking news, natural disaster news or politic news, the year the news occurred, and whether a topic is trending. We also include some known rumour tweets from snopes.com, a site that is dedicated to investigate rumour news. After pre-processing the raw data, the news attributes distribution for the final dataset is shown in Table 2. It can be seen that tweets are evenly distributed in terms of news type, year, and ‘trending or not’, and so there is not any bias regarding the news attributes.

Table 2 Tweets news attributes distribution

News attribute	**Value**	**#**	**%**
News type	Breaking news	509	33.8
	Natural disaster	500	33.2
	Politic	499	33.0
Year	2011	374	24.8
	2012	375	24.9
	2013	377	25.0
	2014	382	25.3
Trending	Trending	781	51.8
	Not trending	727	48.2

4.3 Features

The features reported by readers are features of the tweet message itself, content-based and source-based. For features stated in the free-text format, we applied a summative content analysis based on the list of features identified beforehand (Hsieh, 2005). Table 3 (Column 2) lists the features reported by readers when making their credibility judgements. Since the features are sparse, it is hard to analyse their influence for reader’s credibility judgements. Therefore, we categorise the features into five categories and will use the feature categories in our analysis of the features:

- **Author**: features regarding the person who posted the tweet, including Twitter ID, display name, and the avatar image;
- **Transmission**: features in a tweet message for broadcasting on Twitter;
- **Auxiliary**: auxiliary information external to the textual message, including URL links, pictures, or videos;
- **Topic**: words and phrases indicating the search topic or news type, including search keywords and alert phrases such as “breaking news”;
- **Style**: writing style of a tweet, including language style and message style — expressing an opinion or stating facts.

4.4 Findings

4.4.1 Information credibility: reader’s perception versus automatic prediction

We compare the credibility ratings for 1,510 tweets, given by readers and by the automatic credibility prediction tool TweetCred. Since seven readers judge each tweet, we aggregated the credibility judgements, and consensual voting determines the credibility level of tweets. Tweets that do not have a consensus judgement are discarded from the list. We also collected the real-time credibility prediction score by TweetCred for the same tweets shown to the readers. However, at the time when we ran TweetCred, some tweets were no longer available and therefore discarded for our study.

Overall, 1,317 tweets are used for this analysis. From the 193 deleted tweets, 113 tweets are no longer available on Twitter, and 80 tweets do not have a consensus judgement by majority vote. We calculated the agreement between the two lists of credibility levels of news tweets using Cohen’s Kappa. The test shows that both human and tool have a slight agreement regarding the credibility level of news tweets where, Cohen’s kappa = 0.04. The agreement matrix between the two is shown in Table 4.

Table 3 Features reported by readers to judge credibility for news tweets

Category	Feature	Description
Author	Tweet author	Twitter ID or display name e.g. Sydneynewsnow
Transmission	User mention	Other Twitter user's Twitter ID mentioned in the tweet starting with the @ symbol e.g. @thestormreports
	Hashtag	The # symbol used to categorise keywords in a tweet e.g. #Pray4Boston
	Retweet	Contain the letters RT (retweet) in the tweet and the retweet count
Auxiliary	Link	Link to outside source - URLs, URL shortener
	Media	Picture or video from other sources embedded within the tweet
Topic	Alert phrase	Phrase that indicates new or information update regarding a news topic - e.g. Update
	Topic keyword	The search keyword regarding a news topic e.g. Hurricane Sandy
Style	Language	The language construction of the tweet (formal or informal English)
	Author's opinion	Tweet that conveys the author's emotion or feeling towards the news topic
	Fact	Factual information on the tweet regarding the news topic

Although the credibility level from both TweetCred and readers are more on the credible side, it is clear that readers are more trusting in believing news tweets as credible. Meanwhile, TweetCred gives mixed credibility prediction with 'somewhat credible' being more prominent than the other two credible levels. To understand what makes the difference, we studied the features used by readers, the TweetCred tool and other automatic credibility prediction system.

With the TweetCred tool, the top 10 features include not only the surface features in the tweet textual content visible at a first glance, but also other external features, including author's location provided in their profile and author's friends/followers list that can be found on the author's profile page (Gupta et al., 2014). In another study regarding automatic information credibility prediction of tweets by Castillo et al. (2011), they described two feature groups very relevant for assessing credibility level of tweets. The two feature groups are the propagation subset including the propagation-based feature and the fraction of retweets, and the top-element subset including the fraction of tweets that contain the most frequent URL, hashtag, user mention, or author. The two feature groups mostly include derived features beyond the surface features available in the tweets.

In contrast, readers report a direct approach based on the first impression in the choice of features they use to decide the credibility level of tweets. In previous work, when readers are asked regarding their general approach and features they use to help them decide the credibility level of tweets, the readers listed features they immediately see in the tweets (Shariff et al., 2014). None of the readers describes looking deeper regarding the credibility of the author or the news topic. This behaviour or preferences are also reported by Morris et al. (2012) where they had to prompt their user study's participants to click on the URL links provided on the tweet or to click on the author's name to get into the author's profile page. Clicking and analysing the URL links would help readers make better credibility judgement as the information may come from shifty websites that aim to deceive readers into spreading tweets with devious URL or as part of a phishing attack modus operandi (Dadkhah et al., 2016).

Table 4 The credibility ratings for reader's perception and TweetCred prediction

		TweetCred			
		Very credible	Somewhat credible	Not credible	Total
Readers	Very credible	256	654	67	977
	Somewhat credible	51	230	50	331
	Not credible	1	4	3	8
	Total	308	888	120	1316

4.4.2 Correlation analysis

The correlation analysis for individual demographic attributes for each data setting (as described in subsection 3.5): Original (O), Binary (B), Categorical (C), and the credibility perception is shown in Table 5. At the original data setting, Education and Location are significantly correlated with credibility judgement, $\mathcal{X}^2$ = 49.43, p<0.05 and $\mathcal{X}^2$ = 80.79, p<0.05. Only Location is significantly correlated with all levels of partitioning.

Table 5 Demographic profiles and credibility perception chi-square results

Demographic	Data setting	Credibility	
		$\mathcal{X}^2$	*p-value*
Gender	Original	1.51	0.68
	Binary	1.51	0.68
	Categorical	1.51	0.68
Age	Original	14.87	0.25
	Binary	4.68	0.20
	Categorical	9.84	0.13
Education	Original	49.43	9.20E-5
	Binary	4.78	0.19
	Categorical	12.29	0.20
Location	Original	80.79	2.92E-12
	Binary	39.62	1.29E-8
	Categorical	80.33	1.39E-13

A post hoc analysis on the interest value of cells in the contingency table *Education* × *Credibility* for the original data found that the cell contributing most to the $\mathcal{X}^2$ value is readers with a 'Professional certification', who commonly gave 'not credible' judgements. In regard to the contingency table *Location* × *Credibility*, we found there was a correlation between readers from the African continent and the 'cannot decide' credibility perception in the original and the categorical data setting with a positive dependence. Both cells interest values are far higher than 1, indicating strong dependence for both correlations. In the contingency table for *Location* × *Credibility* in the binary data setting, the interest value in each cell is close to 1, therefore there is no strong dependence.

We then conduct multi-way correlation analysis between combinations of demographic attributes and credibility judgements. Since Location is significantly correlated with all data levels, due to the upward closeness of $\mathcal{X}^2$ statistics (Section 3.5), we will not analyse combinations including Location. The correlation result for the rest demographic attribute pairs is shown in Table 6. In analysing the combination of demographic attributes, Bonferroni corrections of the p-values (p<0.003) are applied (Wright, 1992).

Table 6 Chi-square result for demographic attribute pairwise correlation

(a) (Age, Gender) & (Education, Gender)

Demographic attribute			Credibility	
			$\mathcal{X}^2$	*p-value*
Gender	Age	O	107.71	2.24E-22
		B	77.40	1.07E-13
		C	82.18	5.23E-16
	Education	O	105.89	1.32E-9
		B	48.67	2.57E-12
		C	61.80	2.42E13

(b) Age, Education

		Credibility	
Age	**Education**	χ^2	*p-value*
O	O	1791.23	7.75E305
	B	763.96	4.91E-164
	C	1579.96	0.0E0
B	O	105.89	1.47E-20
	B	2.18	0.13
	C	47.96	2.17E-10
C	O	1732.96	0.0E0
	B	749.53	1.35E-154
	C	1549.49	7.75E-305

Table 6(b) shows that only for the binary setting the (Age, Education) pair is not significantly correlated. Therefore, we further analyse the correlation of the (Age, Education) pair with credibility judgements. The correlation analysis outcome for *Age* × *Education* × *Credibility* is χ^2 = 3.70, p>0.003, accepting the null hypothesis that the three variables have an insignificant correlation. The result indicates that the joint independent demographic attributes of Age and Education in the binary setting do not correlate with the credibility judgements.

Table 7 News attribute correlation with reader's credibility perception

News attribute	**Credibility**	
	χ^2	*p-value*
News type	93.75	5.04E-18
Year	61.89	5.78E-10
Trending	8.09	0.04

To determine the correlation between the news attributes and reader's credibility perception, we continue using Chi-square Independence Test. Table 7 shows the correlation result between tweets news attributes and reader's credibility perception. As what we hypothesised, all of the news attributes are significantly correlated with credibility judgements. We do a posthoc analysis to determine the interest value for each contingency table that contributes the most to the significant χ^2 value. In the contingency table of *News Type* X *Credibility*, we find tweets that report regarding 'breaking news' being perceived as 'very credible' by readers shows a strong positive dependence on the chi square result. As for the contingency table *Trending* X *Credibility*, the strong dependence comes from 'trending' tweets with 'very credible' judgement by the readers. In the last contingency table, *Year* X *Credibility*, tweets that received 'somewhat credible' judgement from the readers and reporting about news occurring in 2014 have a positive dependence in the correlation between the two variables.

We then conduct a multi-way correlation analysis between the combination of reader's demographics and news attributes with reader's credibility perception. In analysing the combination of demographic attributes and news attributes and also for the multi-way correlation test, Bonferroni corrections of the *p-values* where p<0.001 are applied due to the multiple hypotheses being tested. We discover that all attributes from both variables do not correlate with each other at all demographic data setting. Table 8 shows the correlation result between reader's demographics at original data setting and news attributes since all the other data settings achieved a similar result. Thus, we will only focus on the demographics original data setting combination with news attributes for the multi-way correlation test.

The results of the correlation analysis are shown in Table 9. All the multi-way correlation test results do not give significant correlation based on the corrected p-value (p<0.001). The result indicates that readers demographic paired with the news attributes do not significantly correlate with the credibility perception. However, at the variable's individual attribute, reader's age and their geo-location paired separately with the year the news occurred are found to correlate significantly with the reader's credibility perception.

Table 8 Chi-square results between reader's demographics and news attributes

		News attributes					
		News type		Year		Trending	
		χ^2	*p-value*	χ^2	*p-value*	χ^2	*p-value*
Demographic	Gender	1.24	0.54	4.84	0.18	0.34	0.56
	Age	4.36	0.82	9.48	0.66	6.63	0.16
	Education	14.45	0.27	23.5	0.17	6.24	0.40
	Location	3.99	0.86	13.6	0.33	2.01	0.73

The combination of the tweet's news type and the reader's location also shows a significant correlation with credibility perception. We further investigated the association between reader's demographics and news attributes at the item set level regarding the reader's credibility perception using association rule mining. We set the minimum support to 1% and set the credibility perception as the consequent for associate rules. The extracted rules are then pruned for redundant association using the algorithm proposed by Ashrafi et al. (2004).

Table 9 Correlation between combination of reader's demographics and news attributes with credibility perception

Demographic	News attribute	Credibility	
		χ^2	*p-value*
Gender	News type	6.94	0.33
	Year	8.43	0.49
	Trending	7.38	0.06
Age	News type	35.53	0.06
	Year	53.06	0.03
	Trending	18.59	0.10
Education	News type	47.81	0.09
	Year	64.56	0.15
	Trending	16.92	0.53
Location	News type	38.35	0.03
	Year	55.16	0.02
	Trending	17.17	0.14

Table 10 shows the top 10 association rules ordered by lift. From the table, the most interesting rule shows that female readers with a higher education level (Bachelor's degree) for trending politic news are associated with the credibility rating of 'somewhat credible'. Meanwhile, trending news that occurs at earlier years, in 2012 and 2013 (this user study was conducted in 2014) are associated with the 'very credible' credibility level (Row 5 - 8). Although female readers find trending politic news as 'somewhat credible', they perceive trending natural disaster news topics as 'very credible' (Row 4). On the other hand, male readers are associated with perceiving trending breaking news topics occurred in 2013 as 'very credible' (Row 8).

To easily view the interesting antecedent and consequent rules ordered by lift, we visualise the rules using grouped matrix plot as shown in Fig. 2. This visualisation groups rules based on similar antecedents that are statistically dependent on the same consequent. The antecedents consist of the most important item in the group, the number of other items in the group and the number of rules is displayed as the column labels. The row labels on the right-hand side (RHS) are the consequent shared by the groups. For example, in the first column, we find the first three association rules shown in Table 10 grouped together since the rules have the same consequent of the 'somewhat credible' credibility level. Politic is the most important item in the group combined with 8 other items.

Table 10 Associations of demographic and news attributes towards credibility perception

Association rules	**Support (%)**	**Lift**
{news type=Politic, trending=Trended, gender=Female, education=Bachelor's degree} → {credibility=Somewhat credible}	1.0	1.6
{news type=Politic, trending=Trended, age=20-29 years old, location=Europe} → {credibility=Somewhat credible}	1.0	1.5
{gender=Male, education=High school, location=Asia} → {credibility=Somewhat credible}	1.7	1.5
{news type=Natural disaster, gender=Female, location=North America} → {credibility=Very credible}	1.1	1.4
{news type=Breaking news, trending=Trended, year=2013, age=20-29 years old} → {credibility=Very credible}	1.1	1.3
{news type=Breaking news, year=2012, location=South America} → {credibility=Very credible}	1.1	1.3
{year=2012, gender=Male, education=Technical training} → {credibility=Very credible}	1.0	1.3
{news type=Breaking news, trending=Trended, year=2013, gender=Male} → {credibility=Very credible}	1.7	1.3
{year=2013, gender=Male, education=Technical training} → {credibility=Very credible}	1.0	1.3
{gender=Male, education=Technical training, location=Europe} → {credibility=Very credible}	1.6	1.3

In this plot, 346 non-redundant association rules are grouped into 10 groups. The lift value, represented by the colour of each balloon, is the aggregated interest measure of each group. The darkest colour indicates the most interesting rules at the top left corner on the left-hand side (LHS). The size of the balloon shows the aggregated support value.

The circle at the top-left corner indicates a group of three rules where politic news, the most important item, combined with eight more items most likely be perceived as ‘somewhat credible’ by readers. In contrast, at the bottom of the plot, there are much more circles, indicating several rule groups with ‘very credible’ as the consequent. The prominent items contained in the group of rules associated with the ‘very credible’ rating include breaking news, male readers, and readers from South America. On the other hand, there are rules regarding the politic news with high support, their association with the very credible rating as measured by lift is not that strong (the large light circle at the bottom right).

In regard to the last research question, Table 11 shows that all demographic attributes are significantly correlated with credibility perception features reported by readers. In the last column of Table 11, for the analysis of demographic attributes and the Transmission feature, as over 20% of expected values of the contingency table have expected values of less than 5, Fisher's Exact Test is used (McDonald, 2009). Table 11 is based on demographic data at the original setting, and similar results are obtained for data at binary and categorical settings. As all demographic attributes are correlated with credibility perception features, due to the upward closedness of the chi-square statistic, any combination of demographic attributes is also correlated with the credibility perception features.

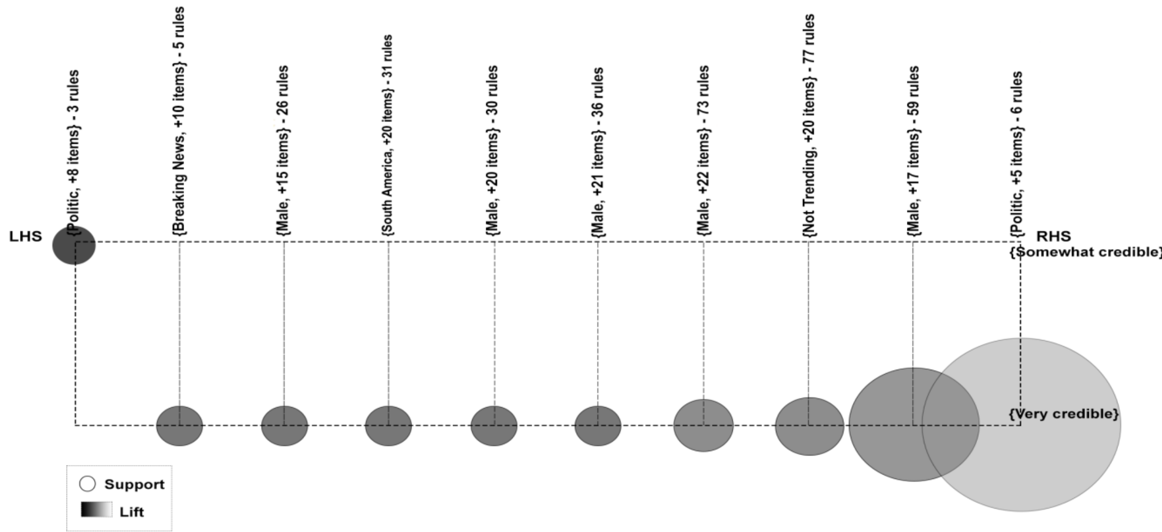


Fig. 2 Grouped matrix-based for 346 association rules with $\boldsymbol{k = 10}$ groups

Table 11 The chi-square correlation between demographics and features used in credibility perception

Demographic			**Feature categories**		
	Author	Topic	Style	Auxiliary	Transmission
	$(\mathcal{X}^2)$	$(\mathcal{X}^2)$	$(\mathcal{X}^2)$	$(\mathcal{X}^2)$	(p)
Gender	0.01	***18.15	***23.27	1.59	0.59[#]
Age	***16.63	***26.65	***41.99	8.65	1.00[#]
Education	11.12	***31.87	***50.12	**16.53	*0.03[#]
Location	***46.87	***83.81	***67.35	***13.60	1.00[#]

[#] Calculated using Fisher's Exact Test
* p<0.05, ** p<0.01, *** p<0.001

Topic and Style features have the most significant correlation with the demographic attributes while the Transmission feature has the least significant correlation with demographic attributes. *Age* and *Location* are significantly correlated with Author, and *Education* and *Location* are correlated with Auxiliary features. Meanwhile, only *Education* has significant correlation with Transmission. We were curious to know if there is a combination of features readers reported to use when perceiving the credibility level of tweets. Using association rule mining to find the frequent combination of features (Agrawal et al., 1993), we found that Transmission, Author, and Auxiliary are frequently used with other features. Table 12 shows the frequent features that meet the support threshold of 1% or 90 times. A support threshold helps to eliminate uninteresting patterns (Tan et al., 2005).

Table 12 Frequent patterns for feature categories

Frequent patterns	Support (%)
Topic	14.1
Style	12.7
Topic, Style	6.1
Auxiliary, Style	5.2
Auxiliary, Topic	4.7
Auxiliary, Topic, Style	4.6
Auxiliary,Topic,Style,Transmission	3.7
Auxiliary,Topic,Transmission	2.7
Author	2.7
Author,Auxiliary,Topic,Style, Transmission	2.6
Topic,Style,Transmission	2.5
Style,Transmission	2.0
Auxiliary,Style,Transmission	1.9
Author,Topic,Style	1.8
Author, Style	1.8
Topic,Transmission	1.6

5 Discussion

This study provides insight regarding reader perception of information credibility of news on Twitter, in terms of the interaction among reader demographics, news attributes and tweet features. Our user study is conducted on a crowdsourcing platform, inviting participants from different continents and of various demographics. The richness of the data allows us to evaluate the correlation of reader's demographics, news attributes and tweet features with their perception of credibility for news tweets.

The differences in credibility levels by reader's perception and by automatic prediction are obvious. Readers are found to give more 'very credible' judgements while the automatic credibility prediction tool produces more 'somewhat credible' ratings. To understand the contributing factors for such differences, we further investigated the features used for credibility judgements by readers and the automatic prediction tool.

Our investigation revealed that automatic credibility prediction indeed uses metadata, or features that are not readily available to readers on the Twitter platform, such as the reputation of the external resources by the URL provided on the tweet message or the author's friend/follower lists. Also, at the binary level (credible and not credible), both the tool and readers agreed that news tweets are believable as true (credible). Indeed, both readers and the automatic tool only labelled about 15% of the rumour tweets as 'not credible'. This result helps explain why so many misinformation and rumour tweets are propagated on Twitter (Bruno, 2011; Jin et al., 2013; Sakamoto et al., 2014; Starbird et al., 2014).

Reader's demographics are found to correlate with their judgement on the credibility level of news tweets. We discover that reader's education background and their geo-location have significant correlation with credibility judgements. This finding is different from other studies (Greer and Gosen, 2002; Kang et al., 2015; Yang et al., 2013), as these studies do not find a significant correlation between tweet credibility perception and the education background. From our analysis, readers with a 'Professional certificate' and who perceived tweets as 'not credible' are the ones that contribute to the significant $\mathcal{X}^2$ result. It is likely that education background may be connected with experience and thus such readers are more careful in making credibility judgements. Another possible reason may be the absence or a low number of higher education level participants in past studies.

Although other researchers found that location is correlated with credibility judgements in general, our dataset of international readership further shows that readers from Africa especially have positive association with the 'cannot decide' credibility judgement. The political conflicts in countries on the Africa continent may have influenced the sceptical attitude towards media by the readers (Cozzens and Contractor, 1987). Therefore, tweets that readers find ambiguous resulted in their indecisive judgements on the tweet credibility (Rassin and Muris, 2005). Other demographic attributes age and gender are not correlated with tweet credibility perception, which is a result similar to the work by Cassidy (2007). Moreover, the combination of age and gender does not have any significant correlation with tweet credibility perception either.

News attributes, including the news type, the year the news taking place and whether a trending topic, also have significant association with reader's credibility perception. We further found that trending news and breaking news are associated with reader's 'very credible' rating. Morris et al. (2012) showed that their participants have more confidence in the credibility of tweets on trending topics due to the similarity of contents between the tweets and the trending topics. Furthermore, Twitter is one of the fastest social platforms for reporting breaking news and spreading the news. Thus it is likely that Twitter readers find breaking news tweet highly credible (Broersma and Graham, 2013; Hu et al., 2012). However, tweets for news events occurred in 2014 (the year we conducted this user study) have positive association with the 'somewhat credible' credibility rating. This result is likely due to the inconsistent news information reported by twitterers and by the news media, as the 2014 news topics are still progressively updated. The result gives a new view regarding the way readers perceive the credibility level of current news events in contrast to old news events, while other research uses only current news tweets (Gupta and Kumaraguru, 2012; Hu et al., 2012; Kang et al., 2015; Kwak et al., 2010).

We found that selected paired attributes correlate with reader's credibility perception of news tweets. At the individual attribute level, readers have different perception of news credibility. While natural disaster and breaking news are perceived as 'very credible' by both genders, female readers find it difficult to believe political news tweets. The reason is not that female readers are not devoted readers of political news, as they are often portrayed in fictions, but that female readers are more critical in their judgement regarding politics, which made them more cautious in believing political news (Zboray and Zboray, 1996). Young adults are also capable of assessing the credibility of news tweet as experienced readers (Rieh and Hilligoss, 2008). These findings show a new perspective in understanding the relationship between factors such as reader's background and news attributes, and reader's credibility judgement.

The way an author writes his/her tweets also give different credibility impression to readers with different demographic backgrounds. We find that all demographic attributes are significantly correlated with the topic features: topic keyword and news alert phrase, and the tweet writing style. More than 26% of credibility judgements rely on topic and style features. Features that are used in broadcasting tweets – the auxiliary features and author features – seem to be not considered by readers when judging the tweets' credibility level. Our results show a perspective different from studies by Castillo et al. (2011), Hu et al. (2012), Liu (2004) and Sundar (1998). We also find that auxiliary and author features are mostly combined with other feature categories when readers make credibility judgements of news tweets, a result that is missing in other studies where these features are studied separately.

6 Conclusions

Although research on Twitter information credibility has been reported, most work focuses on the automatic prediction of tweet credibility. Our focus is on understanding Twitter readers, and whether news attributes and tweet features affect reader's credibility judgements. In this study, we identified that the difference between automatic credibility prediction tool and reader's credibility perception is due to reader's behaviour of focusing on surface features shown in tweet contents. This result can help educate readers to be more cautious of the information credibility on Twitter. Our rich data also allows us to provide new insights into the correlation between reader's demographic attributes, news topics and tweet credibility judgements, as well as the features readers used to make those judgements. The findings from this study present the features in tweets that correlate with readers from different demographic background and with their credibility perception of tweets. This could provide guidelines for tweet authors, especially public relation officers or freelance journalists to design their news tweets according to their target readers so that tweets would be perceived as credible.

Our study has several limitations. The first limitation is the skewed gender distribution in our dataset. While conventional qualitative user studies allow researchers to control the gender balance in user studies, user studies on the crowdsourcing platform often leads to gender imbalance (Kang et al., 2015; Peer et al., 2016). We note that implications of this imbalance towards credibility analysis are not clear and needs to be further examined. A second limitation is the fact that our study focused only on three news types; breaking news, natural disaster and politics. To conduct general study on Twitter credibility perception, future work can address a wider range of news types that include scientific, sports, technology and entertainment. Third, due to the sparsity of reader's geo-location data, our analysis is conducted on data aggregated at the continent level. More data would allow fine grained analysis at the country level.

Future research will explore explicit feature criteria for tweets credibility perception on wider range of news types and the implication of reader's experience in tweets credibility perception. It is also important to study reader's behaviour for their perception of tweet credibility.

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