Determining the Role of Nonverbal Tokens in the Spread of Online Information

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Abstract

Individuals and society continue to suffer as the fake news infodemic continues unabated. While existing research has focused on the verbal part (plain text) of fake news, the nuances of nonverbal communication (emojis and other semiotic tokens) remain largely understudied. We explore the relationship between fake news and semiotic tokens in this work through two studies. The first study finds that information with emojis is retweeted 1.28 times more and liked 1.41 times more than information without them. Additionally, our research finds that tweets with emojis are more common in fake news (49%) than true news (33%). We also find that specific semiotic tokens are more popular with fake news compared to true news. In our second study, we conducted an online experiment with true and fake news (N=99) to understand how the functional usage (replace/emphasize) of semiotic tokens affects the spread of information. We find that when an emoji replaces a verbal token, it is liked less (p<0.05) or equal to information without a nonverbal token (control condition), and when an emoji emphasizes a phrase, it is liked more or equal to the control condition. These effects are observed only for fake news. Functional usage of emojis did not affect the diffusion of true news in our study (p >0.05).

1. Introduction

The infodemic of fake news continues to affect society unabatedly. It caused disruptions in the democratic process by manipulating voters before and after the two most recent US presidential elections, and currently it affects healthcare severely in the middle of a global pandemic by spreading fake news about topics ranging from bleach as a cure to vaccines with microchips. Clearly, entities that spread fake news have no intention of slowing down, creating a significant threat to society. As we continue to investigate the spread of fake information online, many studies have focused on user behavior [1, 2, 3] and automated fake news detection [4, 5]. However, the key focus of most of these studies has been on the verbal component (i.e., plain text) of fake news. Semiotic tokens/emojis represent an additional element of online communication that can enhance meaning. We refer to emojis as nonverbal tokens or semiotic tokens and use these three terms interchangeably in this work. Emotions are a vital component of human communication [6]. Without non-verbal tokens, it is sometimes difficult to understand the emotion behind online communication (e.g., tweets, posts, stories). As shown in Table 1, the emotion of this author is not entirely known to the reader without semiotic tokens.

Condition	Sentence	Conveyed emotion
No non-verbal cue	Are you coming?	emotion unknown
Anger emoji	Are you coming? 😡	anger
Thinking emoji	Are you coming? 🤔	curiosity
Grinning face emoji	Are you coming? 😀	happiness

Table 1. These sentences show three different emotions (anger, curiosity, and happiness). It is almost impossible to know the emotional state of the speaker/writer based on the first sentence alone, which does not contain any nonverbal cues for the reader.

Semiotic tokens such as emojis are pervasive on the internet and convey emotions that supplement verbal text. Some studies have shown that non-verbal semiotic tokens such as emojis have a positive impact by helping internet users develop a personal connection with the message [7, 8, 9], express emotion [10], connect with brands [11], reduce anxiety levels in online classrooms [12], and make social movements more relatable [13]. However, emojis have been used for causing harm as well, creating malware using specialized keyboards [14], and creating signals for human traffickers [15, 16]. Emojis can reduce misinterpretations in communication [17], present emotion, and make intentions less confusing; however, Miller et al. [18] suggest that information from communication artifacts that contain emojis are perceived as less credible, and emojis themselves can be misinterpreted. While emojis sentiments have been used as a feature to analyze the trustworthiness of a tweet, their impact on information propagation is not fully known. We perform two studies in this work to understand the role of emojis in information propagation. In the first study, we collect, process, and analyze tweets from the fact-checking platform Snopes. We measure the effect of nonverbal tokens on information propagation. In the second study, inspired by the Pictograms-Ideograms-Emojis (PIE) framework [19], we explore emojis functional role in the text. The rest of the paper is organized as follows: section 2 discusses the relevant literature review and research questions, sections 3 and 4 describe studies I and II respectively along with results, section 5 discusses the research and practical implications of this work, and section 6 provides the conclusion.

2. Literature Review

2.1. Fake News

Fake news is defined as forged or made-up information aiming to look like information from news media in structure but lacking in the execution process and purpose [20] . Although fake news gained popularity after the 2016 US elections, similar techniques were used during the Crimean annexation through social media platforms [21]. Several methods have been developed to understand fake news and detect it online. Detecting fake news automatically on social media platforms is a key technique to reduce the spread or impact of fake news [22], which has been shown to travel six times faster than true news [1]. Some studies have combined linguistic cues with deep learning to create neural network models to detect fake news [23, 24]. Such automated techniques help develop models to detect fake news and estimate how fast it spreads. Studies have shown that humans are more responsible for spreading fake news than other mediums such as bots [1]. As such, several studies have also focused on understanding human behavior towards fake news. Studies have found the effect of source credibility on information propagation [25], information format [2], source-endorser credibility [3], and information variance [26]. However, these studies have focused on the textual content alone. Several studies have shown that content with emotions such as awe or amusement is highly shared online[1]. However, the effect of non-verbal tokens that influences humans to share information is understudied.

[1]https://bit.ly/35mUeAP

2.2. Non-verbal Communication

Emojis are a critical nonverbal cue on social media. An estimate of 5 billion emojis are sent on Facebook each day . Understanding how these non-verbal tokens are used and knowing their effect on a social media post can help us understand the nuances of information propagation. Several studies have explored the role and impact of these non-verbal tokens online across several different contexts.

Whether in text or as a reaction (e.g., Facebook *like* emojis), features such as emojis are an important part of online information such as tweets and posts [27]. Adding emojis in online feedback improves the positivity of the message being shared [28]. Emojis have also been known to make critical feedback be perceived positively when they accompany the text [28]. They also improve the perception of the source sharing the message [28]. Studies have leveraged various emotions from emojis to classify whether a news article was fake or not in the context of fake news. Others have used emoji sentiment as a feature to analyze the trustworthiness of a tweet [29] . Studies have also used emojis of different classes and emotional characteristics to profile fake news spreaders using emojis directly [30] or converting them into textual descriptions [31]. Emojis have also helped in determining the gender of the fake news spreader [31]. However, emoji-based sharing (e.g., Facebook reactions) has been shown to create more confusion [32].

2.3. Research Gaps and Research Questions

While existing studies have focused on understanding how behavior and attitudes are affected by different types of information, their focus has been mainly on textual information alone. Studies utilizing emojis in different contexts by using them directly as Unicode characters or converting them into textual form do not inform us about emojis impact on information propagation. How emojis support or are supported by text around them is also not known fully. Emojis can have different functional roles in the text [19]. In this study, we define the functional role of emoji as *replace* if the emoji replaces or acts as a substitute for a word or phrase in the text and *emphasize* if it emphasizes an existing word or phrase in the text. Based on the research gaps and literature review, we pose the following research questions:

(I) What is the role of nonverbal tokens in the spread of information?

(II) What are the different types of semiotic tokens used in fake news?

(III) How does functional usage of semiotic tokens affect the spread of information?

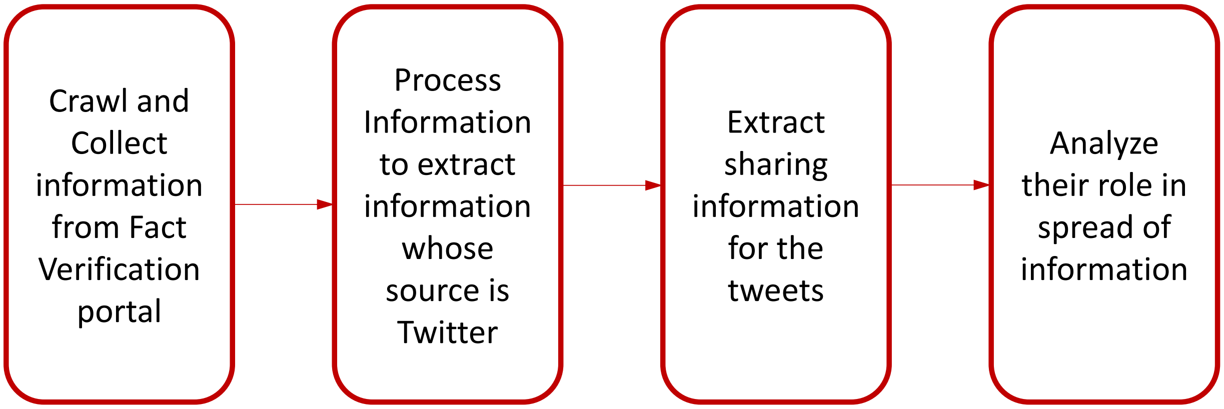

Figure 1. Overall research methodology for study I. Data is collected, cleaned, processed, and analyzed to understand the role of non-verbal tokens.

3. Study I- Understanding the role of Non-Verbal communication in the spread of information

This section addresses the first two research questions- about the roles and types of nonverbal tokens in the spread of information.

3.1. Research Methodology

Method: Our overall research methodology is described in Figure 1. This experiment was conducted using a four-step process. First, we crawl and collect data from the popular news verification website, `Snopes.com`. Data from *Snopes* exists in an unstructured format. We converted this unstructured data into structured data by extracting the labels (true, fake, or something in between), links, and social media URLs from the raw data. From the structured data, we use only those articles that contained a valid Twitter link. Using the Twitter API, we then collected all the text of these tweets and features such as the number of likes or retweets. These tweets were separated into two groups- one containing nonverbal tokens and the other without them. We then applied various statistical methods to analyze and understand the effect of nonverbal tokens on the spread of information. The dataset is described in detail next.

Dataset description: We crawled and collected data from the popular fact verification website Snopes.com. Snopes was chosen as our data source because of the variety of news it represents. In total, Snopes debunks fake news from 45 different domains. Additionally, Snopes has debunked online fake news since 2001, providing a rich dataset. Dataset statistics are provided in Table 2.

Description	Value
Total Tweets form Snopes	7,217
Total after collecting from Twitter	3,615
Total Tweets with emojis	305 (8.43%)
Total Tweets without emoji	3,310 (91.57%)
Total Emojis in tweets	570
Total unique emojis in Tweets	194

Table 2. Dataset description for study I

3.2. Results

We observed that 8.43% of the tweets contained one or more emojis, while 91.5% of the tweets did not contain an emoji. Tweets with emojis were retweeted 7,472 and liked 26,837 times on average, while tweets without emojis were retweeted 5,811 times and liked 18,919 times. This result suggests that tweets with emojis spread more (RT- 128.58%, Like- 141.85%) than tweets without emojis. Amongst the tweets with emojis, 49% of the tweets were associated with fake news, 33% with true news and 18% were a mix of true and fake or unproven. Thus, we see that nonverbal tokens are associated more with fake news compared to true news. Our results are summarized in Table 3. We also investigated the most popular emojis used in these tweets (Table 4). Further investigation of these emojis revealed that not all emojis are equally utilized: while certain emojis are associated with fake news, others appear in the context of true news (Table 5).

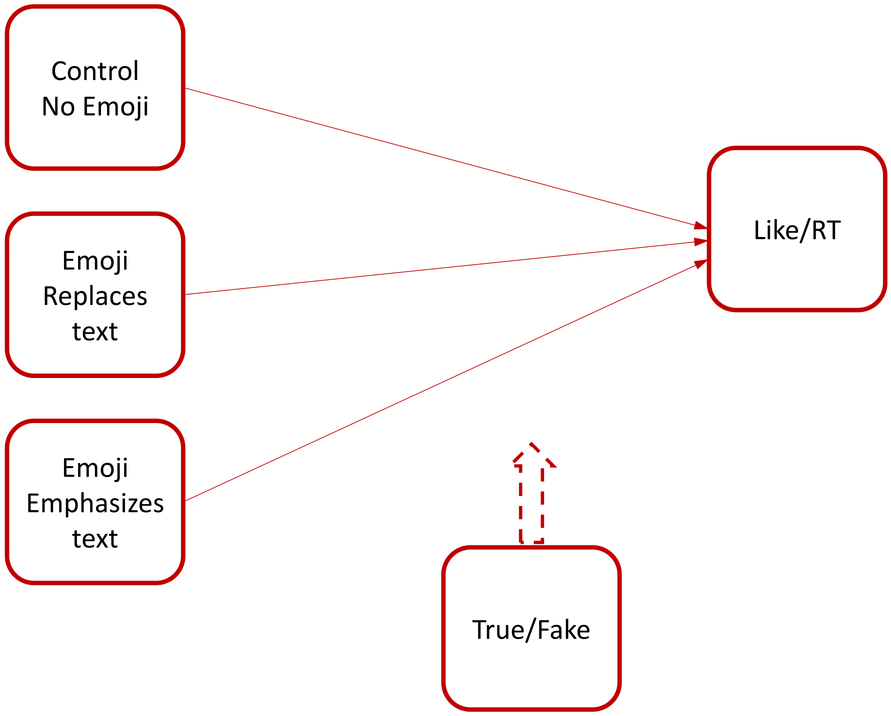

Figure 2. Study II research model

Descriptive statistics	Value
Total RT for Tweets with emojis	2,279,139
Average RT for Tweets with emojis	7,472
Total LIKE for Tweets with emojis	8,185,455
Average LIKE for Tweets with emojis	26,837
Total RT for Tweets without emojis	21,004,104
Average RT for Tweets without emojis	5,811
Total LIKE for Tweets without emojis	68,375,734
Average LIKE for Tweets without emojis	18,919

Table 3. Results summary of study I

Emoji	Percentage Use
😂	8.42%
🇺🇸	5.43%
👇	4%
🚨	4%
😭	3.68%

Table 4. Most frequent emojis used

Emoji	% association with fake news
😂	67%
🇺🇸	93.54%
👏🏾	100%
🤣	48%
🙏	29%
⬇️	33%

Table 5. Association of emojis with fake information

4. Study II- Understanding the functional role of non-verbal tokens in information propagation

4.1. Research Methodology

We conducted an experiment to measure the effect of functional usage of emojis in the tweet. Figure 2 shows the overall experiment model. A pilot study was conducted first to identify areas of improvement in the experiment design and questionnaire, followed by the main study. The experiment is described in detail next.

4.1.1. Pilot

Method: We conducted a pilot study using 30 student participants from a large south-western university. Participants were presented with four tweets with different political issues (See Appendix), followed by a demographics questionnaire. This study helped us identify several problems that led to additional changes in the main study. We identified that not all participants were familiar with Twitter; this was added as an additional filter for the main study. While sources and their verification status were hidden in the tweets, some participants indicated the source as one of the critical factors in sharing. We added an additional statement in the questionnaire, - the source and its verification status has been blacked out deliberately for this experiment to overcome this challenge. Additionally, Likes and RTs counts for the tweets were set to blank to avoid bias. Some participants indicated the need for RT comments. This was added in the main study. We observed that participants did not Like or RT the articles any differently for the different experimental conditions during the pilots result analysis. Several participants commented in the additional comments of the study section that they share political news very rarely. Our finding from the pilot was consistent with a recent Pew research study [33]. Based on existing studies and results from our pilot, we avoided political topics in the tweets of our main task. We have selected topics from or inspired by content on Snopes.com and other online fact verification portals.

4.1.2. Main Study

Participants: After identifying the issues in the pilot study, we conducted the main study with participants from the online research recruitment platform- Prolific Academic. The participants were compensated monetarily for their time. Prolific Academic was chosen to recruit participants as it provides a unique filter required for this study: we wanted to recruit people who know and use Twitter and know what common Twitter vocabulary like/rt means. All participants in this study were active Twitter users and had shared content multiple times over the last 12 months. Other platforms, such as Amazon Mechanical Turk, provide a filter for selecting participants who have a Twitter account but provide no information about the users being active or sharing content on the platform. A total of 99 people participated in this study. All participants were US residents. Participants demographics are summarized in Table 6 and their social media usage is summarized in Table 7.

Method: In the main study, participants were presented with five tweets. The first was a practice tweet

Demographic	Levels	Percentage
Gender	Female	39.40%
	Male	58.60%
	Non-binary/ Other	2.0%
Age	18-24	13.13%
	25-34	39.40%
	35-44	31.31%
	45-54	11.11%
	>54	5.05%
Ethnicity	Asian	7%
	African American	12%
	Native American	1%
	Other	3%
	White	77%

Table 6. Demographic indicators summary

Social Media	Levels	Percentage
Key sources of online news	News portal alone	20%
	Social Media alone	17%
	Search engine alone (google news and others)	8%
	More than one source type	38%
	Others	16%
Preferred social media platform for information	Twitter	52%
	Facebook	7%
	More than one platform	23%
	Others	18%
Preferred sharing domains	Politics	16%
	Non-Politics	84%

Table 7. Social media usage and preference

(participants were not of informed that); of the remaining four tweets, two tweets were true, and two were fake. Each tweet had three variations. The first was the control condition. Here, no emojis were present in the tweet. The second condition was the replace condition. Here, the words were replaced by an emoji. The third and last condition was the emphasize condition. Here, some phrases in the tweet were emphasized by the emoji. Each participant was assigned tweets randomly and the tweets appeared in random order for each participant. Figures 3, 4, 5, and 6 (Appendix) show the four tweets presented in this experiment.

Dependent Variables: Our dependent variable was a binary question. Participants were shown a tweet and asked: On Twitter, you will like/retweet (RT) the tweet (Yes/No); the RT option also provided participants to add a comment.

Independent and Control Variables: We controlled for belief in the experiment. The measure for belief was adopted from Kim and Dennis (2019) [2]. We asked the participants two 7-point Likert scale questions- I find this tweet credible and I find this tweet believable.

4.2. Results

As we measured our variables between and within participants, we first calculated the inter-class correlation coefficient (ICC) scores for the null models and the random-effects model, with participants as the random factor for our study. An overall percentage of less than 10% indicated no necessity for hierarchical linear modeling. Each tweet was treated as an individual response and analyzed using logistic regression. Overall results for this experiment are described in Table 8 and Table 9. Model 1 (M1) represents results from Tweets shown in Figure 5 and Model 2 (M2) represents results from Tweets shown in Figure 6. We control belief in our experiment. Overall, we find that when emoji(s) replaces word(s) in fake information, it is liked less (Model 1, $p<0.05$, $\beta = -2.46$) or has equal odds (Model 2) of being liked compared to the same tweet with no emojis. When an emoji emphasizes word(s) in fake information, it is liked more (M2, $p<0.05$) compared to the control condition. We performed a chi-square test for both models and found the effects of the experiment conditions to be significant (Table 10 and Table 11) . McFadden's pseudo R2 was > 0.2 for both the models, indicating an excellent fit (McFadden, 1977 p. 35) [34]. No statistically significant effects were observed for true news ($p>.05$) (Figure 3 and Figure 4).

Predictors	**Log Odds**	**p**
(Intercept)	-3.40	0.24
Replace	-2.46	**0.04***
Emphasize	-0.47	0.53
Belief	0.79	**0.001****
Visit_Twitter [2-5 times a day]	0.60	0.56
Visit_Twitter [5-10 times a day]	0.45	0.63
Visit_Twitter [Not everyday]	-12.17	0.99
Visit_Twitter [Once a day]	2.26	0.15
Sharing [Daily]	-0.98	0.70
Sharing [Every few months]	-0.95	0.71
Sharing [Every few weeks]	-1.63	0.57
Sharing [Multiple times a day]	-17.09	0.99
Sharing [Weekly]	-0.38	0.88
Twitter_Hours [3-5 Hours]	0.75	0.42
Twitter_Hours [A Less than 1 hour]	-1.14	0.67
Twitter_Hours [More than 5 Hours]	-0.42	0.63
Observations	99	–
Null Deviance	87.58	–
Residual Deviance	57.59	–
McFadden R2	0.34	–

Table 8. M1 represents results for Figure 5

Predictors	**Log Odds**	**p**
(Intercept)	-24.58	0.99
Replace	-0.004	0.99
Emphasize	3.65	**0.01***
Belief	1.14	**0.002****
Visit_Twitter [2-5 times a day]	0.83	0.48
Visit_Twitter [5-10 times a day]	-1.42	0.26
Visit_Twitter [Not everyday]	3.45	1.00
Visit_Twitter [Once a day]	-0.19	0.91
Sharing [Daily]	16.07	0.99
Sharing [Every few months]	15.81	0.99
Sharing [Every few weeks]	14.81	0.99
Sharing [Multiple times a day]	1.31	1.000
Sharing [Weekly]	16.83	0.99
Twitter_Hours [3-5 Hours]	2.98	**0.04***
Twitter_Hours [A Less than 1 hour]	-14.39	0.99
Twitter_Hours [More than 5 Hours]	0.51	0.68
Observations	99	–
Null Deviance	80.68	–
Residual Deviance	40.02	–
McFadden R2	0.50	–

Table 9. M2 represents results for Figure 4

Factor	DF	Deviance	p
Replace/Emphasize	2	7.47	0.02
Belief	1	14.52	0.001
Visit Twitter Frequency	4	4.21	0.37
Sharing	5	2.30	0.80
Hours spent on Twitter	3	1.48	0.68

Table 10. Deviance is reduced by adding each factor in Model M1. DF represents degrees of freedom or levels in a particular factor.

Factor	DF	Deviance	p
Replace/Emphasize	2	13.89	0.0009
Belief	1	14.52	0.001
Visit Twitter Frequency	4	4.21	0.37
Sharing	5	2.30	0.80
Hours spent on Twitter	3	1.48	0.68

Table 11. Deviance is reduced by adding each factor in Model M2. DF represents degrees of freedom or levels in a particular factor. Functional factors (Replace/Emphasize) play a significant role in reducing the deviance of the model.

5. Discussion

In the first study, we observe that emojis are used more by tweets containing fake information compared to tweets containing true information, indicating that fake news could use emojis as a technique to manipulate readers emotionally. This is further supported when we observe that tweets with emojis are liked and retweeted more compared to tweets without emojis. The emotion in the tweets acts as a catalyst for information diffusion. We also observe that different emojis are associated with fake and true news. Some emojis such (e.g., 👏🏾) appear mostly with fake information, while others (e.g., 🙏) appear mostly with true news. The 😂 emoji, which is the most popular emoji online, appears to be the most popular emoji in our dataset as well. We also observe that emojis with smiley faces are not associated very strongly with fake news or true news. In our second study, we find that emojis had a stronger and statistically significant effect on liking a tweet compared to retweeting. Liking can be a better measure for information diffusion because it is not strongly associated with views as retweeting is. Internet users may like and share differently. Retweeting may be associated with specific issues only while liking is somewhat ambiguous (e.g., like can be sarcastic). Retweeting sensitive topics or extreme views can get an individual in trouble with their workplace or social circle. While like is a softer assertion of the views. Additionally, people retweet only specific domains and it is not possible to know peoples interests in advance.

6. Implications for Research

6.1. Theoretical Implications

In this work, we contribute to the information propagation literature by identifying emojis as an important factor in social media communications. Our work provides empirical evidence to show that information containing non-verbal tokens is more likely to spread on social media than information without non-verbal tokens. This suggests that future studies should account for the effect of nonverbal tokens when trying to understand how information propagates. This perspective is not limited to fake news; other important social impact domains such as hate detection and, cyber-bullying should consider the implications of non-verbal tokens. We also provide empirical evidence that some emojis are associated with true news, while others are associated with fake news. This indicates that within the same social domain, emojis play different roles. Future research should consider this dual nature of nonverbal communication (e.g., in cyber-bullying, one set of emojis may be used by bullies, while another group of emojis may be used by those seeking help from such bullies). In addition, we provide experimental evidence to show the functional role of emojis in the text. Nonverbal communication can be used to express emotion more clearly compared to text without it. In different contexts, the functional role of emojis has a different likelihood of propagating.

6.2. Practical Implications

Our research has substantial implications for practitioners as well. Fake news peddlers are are looking to spread misinformation or harm society continuously. This study encourages organizations to look for patterns in malicious emails to determine if there is a consistent use of certain nonverbal cues, in which case employees can be on the lookout for them. Internal fake news can also be reduced in organizations by looking at these emojis that spread fake news or are a part of it. They can start with the emojis identified in this study as a baseline, but they may have context-specific emojis as well. Social media organizations such as Twitter can also look at emojis and see if something is going viral and has emojis to detect fake news on their platforms.

7. Conclusion

In this work, we investigated the effect of nonverbal communication on information propagation. We collected information from a fact verification portal and examined tweets by separating them into tweets with and without nonverbal tokens. We found that news with non-verbal tokens spreads more compared to tweets without non-verbal tokens. Additionally, we found some nonverbal tokens to be associated more with true information compared to fake news. We also investigated the functional role of nonverbal tokens on the spread of information. We conducted an experiment to determine the effect of a non-verbal token replacing a verbal token, a nonverbal token emphasizing text versus information with no non-verbal token. Here, we found that the functional role of nonverbal communication affected fake news and had no effect on true information. When nonverbal tokens emphasize text, they are like more and when they replace text, they are more liked less compared to text without emojis. Our work has implications for theory and practice.

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8. Appendix

Figure 3. Represents all the three conditions for the given tweet. The first (top most) represents the control condition, the middle represents the replace condition, and the bottom Tweet represents the emphasize condition. This Tweet represents True information.

Figure 4. Represents all the three conditions for the given tweet. The first (top most) represents the control condition, the middle represents the replace condition, and the bottom Tweet represents the emphasize condition. This Tweet represents True information as well.

Figure 5. Represents all the three conditions for the given tweet. The first (top most) represents the control condition, the middle represents the replace condition, and the bottom Tweet represents the emphasize condition. This Tweet represents fake information. Results of this tweet are presented in Table 9 for M1

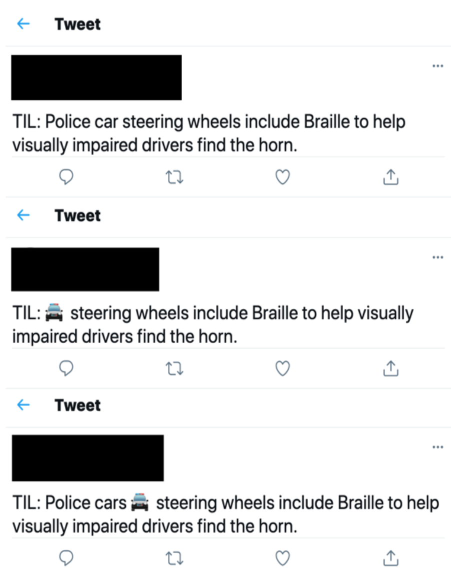

Figure 6. Represents all the three conditions for the given tweet. The first (top most) represents the control condition, the middle represents the replace condition, and the bottom Tweet represents the emphasize condition. This Tweet represents fake information. Results of this tweet are presented in Table 8 for M2