Understanding 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. Current research has focused largely 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 emojis in this work through two studies. The first study found 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 emojis 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 emoji 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).

Keywords: Emoji, Fake News, Paratext, Nonverbal communication

1. Introduction

The infodemic of fake news continues to affect society unabated. 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 (Allcott & Gentzkow, 2017; Pennycook et al., 2021; Vosoughi et al., 2018) and automated fake news detection (Mithun et al., 2021; Oshikawa et al., 2018; Suntwal et al., 2019; Thorne & Vlachos, 2018). However, the key focus of most of these studies has been on the verbal component (i.e., plain text) of fake news. Emojis represent an additional element of online communication that can enhance meaning. Emotions are a vital component of human communication (Ekman, 1992). Without emojis, 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 emojis.

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

Table 1. These sentences show three different emotions (anger, curiosity, and happiness).

Semiotic tokens such as emojis are pervasive on the internet and convey emotions that supplement verbal text. Some studies have shown that emojis have a positive impact by helping internet users develop a personal connection with the message (Agnew, 2017; D Derks & Fischer, 2008; Daantje Derks et al., 2008), express emotion (Willoughby & Liu, 2018), connect with brands (McShane et al., 2021), reduce anxiety levels in online classrooms (Christiansen, 2021), and make social movements more relatable (Santhanam et al., 2019). However, emojis have been used for causing harm as well, creating malware using specialized keyboards (Nichols, 2019), and creating signals for human traffickers (Tong et al., 2017; Whitney et al., 2018). Emojis can reduce misinterpretations in communication (Kaye et al., 2017), increase

URI: https://hdl.handle.net/10125/103303
978-0-9981331-6-4

information diffusion and spread (Hönings et al., 2021), help in multimodal sentiment analyses (Tran et al., 2018), present emotion, and make intentions less confusing; however, Miller et al. (Miller et al., 2016) suggest that information from communication artifacts that contain emojis are perceived as less credible, and emojis themselves can be misinterpreted. Studies have also found contradicting evidence where they also improve the perception of the source sharing the message (Aritajati & Rosson, 2021), indicating that the role of emojis in online communication is not fully understood yet.

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 emojis on information propagation. In the second study, inspired by the Pictograms-Ideograms-Emojis (PIE) framework (Suntwal et al., 2021), 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 the results, section 5 provides the results and discussion, section 6 informs us about the research and practical implications of this work, and section 7 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 (Lazer et al., 2018). Although fake news gained popularity after the 2016 US elections, similar techniques were used during the Crimean annexation through social media platforms (Aral, 2020). 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 (Shu et al., 2017), which has been shown to travel six times faster than true news (Vosoughi et al., 2018). Some studies have combined linguistic cues with deep learning to create neural network models to detect fake news (Horne & Adali, 2017; Wang, 2017). 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 (Vosoughi et al., 2018). 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 (Maasberg et al., 2018), information format (Kim & Dennis, 2019), source-endorser credibility (Suntwal et al., 2020), and information presentation (Osatuyi & Hughes, 2018). 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. However, the effect of emojis that influences humans to share information is understudied.

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 emojis 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 emojis 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 (Zhang & Ghorbani, 2020). Adding emojis in online feedback improves the positivity of the message being shared (Aritajati & Rosson, 2021). Emojis have also been known to make critical feedback be perceived positively when they accompany the text (Aritajati & Rosson, 2021). 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 (Atodiresei et al., 2018). Studies have also used emojis of different classes and emotional characteristics to profile fake news spreaders using emojis directly (Manna et al., 2020) or converting them into textual descriptions (Baruah et al., 2020). Emojis have also helped in determining the gender of the fake news spreader (Baruah et al., 2020). However, emoji-based sharing (e.g., Facebook reactions) has been shown to create more confusion (Albright, 2017).

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 (Suntwal et al., 2021). 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 emojis 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?

3. Study I- Emoji usage in Social Media

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

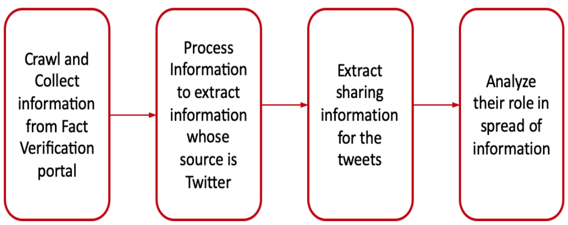

Figure 1. Overall research methodology for study I.

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 crawled and collected data from the popular news verification website, Snopes from 2001 to 2021. from Data from Snopes exists in an unstructured format. We converted this unstructured data into structured data by extracting textual features such as the labels (e.g., true, false, mixture, unproven), links, and social media URLs from the raw data. From the structured data, we use only those articles that contained a valid Twitter link.

We applied a regular expression to extract those articles with twitter links (https://twitter.com/.*?[/status/][0-9]+). Duplicate twitter links were removed at this stage of data cleanup by comparing tweet IDs. Next, using the Twitter API, we then collected the tweet text and engagement features such as the number of likes and retweets. Following which, we separated our tweets into two categories: tweets with emoji and tweets without emoji. We then applied aggregation statistics to each category to analyze how much emojis affected engagement (likes, retweets). The dataset is described in detail next.

Dataset description: We crawled and collected data from the popular fact verification website Snopes.com. Snopes has debunked online fake news since 2001, providing a rich dataset. Snopes was chosen as our data source also because of the variety of news it represents. In total, Snopes debunks fake news from 45 different domains. However, we do not differentiate tweets by domain. Originally, we collected 7,217 tweet IDs from the Snopes website. After querying the Twitter API for the tweet text and engagement statistics, we obtained 3,615 tweets. A total of 3,602 tweets in our original dataset collection had either been deleted by the authors or Twitter moderators. 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

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 on average. This result suggests that tweets with emojis receive more engagement (RT- 128.58%, Like- 141.85%) from users than tweets without emojis.

Among 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 emojis 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).

Descriptive statistics for Tweets	With Emojis	Without Emojis
Total RT for Tweets	2,279,139	21,004,104
Average RT for Tweets	7,472	5,811
Total LIKE for Tweets	8,185,455	68,375,734
Average LIKE for Tweets	26,837	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.

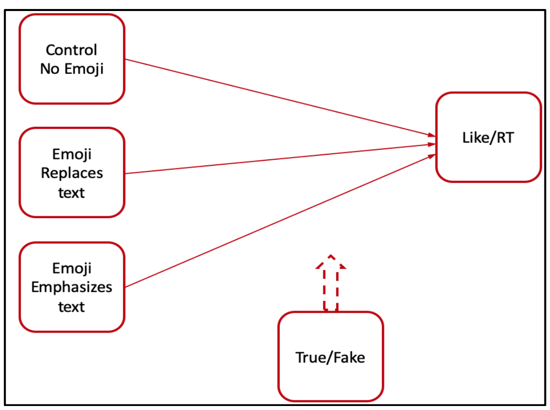

Figure 2. Study II research model

4.1.1 Pilot

Method: We performed a pilot study using 30 student participants from a large south-western university. Participants were presented with four tweets with different societal 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 determined that not all participants were familiar with Twitter, therefore we included this as an extra qualifier to the main study. Despite the fact that sources and their verification status were concealed in the tweets, several participants cited the source as one of the most influential elements in sharing. To circumvent this difficulty, we included an extra line to the questionnaire: "The source and its verification status have been intentionally masked for this experiment." In addition, the Likes and RTs numbers for each tweet were adjusted to zero to prevent bias. Some participants expressed a preference for RT with comments option. This was added to the main study. During the pilot's result analysis, we observed that participants did not Like or RT the articles differently depending on the experimental condition. Several individuals mentioned in the additional comments section of the research that they rarely share political news. Our finding from the pilot was consistent with a recent Pew research study (McClain, 2021). Based on these results from our pilot, we avoided political topics in the tweets of our main study. We 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 completed the main study with participants recruited using Prolific Academic, an online research recruiting site. 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: recruiting people who are familiar with Twitter and shared online content in the last 12 months. This was required because we used common Twitter vocabulary like/rt in our study. All participants in our study were active Twitter users and had shared content on Twitter 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. We recruited 99 participants for this study. We paid $5 per participant for this study. All participants were US residents. All participants completed the attention check questions correctly. No data points were dropped in this study. Participants' demographics are summarized in Table 6 and their social media usage is summarized in Table 7.

Demographic Factor	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

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

Table 7. Social Media usage and preference

Method: In the main study, participants were presented with five tweets. The first was a practice tweet (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 words/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 1A, 2A, 3A, and 4A (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); similar to Twitter platform, the RT option also provided participants to add a comment.

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

5. Results and Discussion

As we measured our variables between and within participants, we first calculated the inter-class correlation coefficient (ICC) scores for the null model and the random-effects model, with participants as the random factor for our study. ICC was less than 10% indicating no necessity for hierarchical linear modeling. We treated each tweet as an individual response and analyzed the data using logistic regression method.

Overall results for this experiment are described in Table 8 and Table 9. Model 1 (M1) represents results from Tweets shown in figure 3A (see appendix) and Model 2 (M2) represents results from Tweets shown in figure 4A (see appendix). 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 R (McFadden, 1977) was greater than 0.2 for both the models, indicating an excellent fit (McFadden, 1977 p. 35). No statistically significant effects were observed for true news ($p>0.05$); See appendix figures 1A and 2A.

In study I, we observe that fake information tweets use more emojis compared to true information tweets. This indicates that fake news could be using emojis as an instrument to manipulate readers emotionally. This finding is further supported when we observe that tweets with emojis are liked and retweeted more compared to tweets without emojis on average. The emotion in the tweets act may support information diffusion or increase user engagement. We also observe that different fake news and true news tweets use different emojis. Some emojis (e.g., 👏🏾) appear mostly with fake information, while others (e.g., 🙏) appear mostly with true news. The face with tears of joy (😂) emoji, which is the most popular emoji online, is 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 study II, we find that emojis had a stronger and statistically significant effect on liking a tweet compared to retweeting. Liking can indicate subtle engagement because it is not strongly associated with views as retweeting is. Retweeting involves more clicks and signifies more engagement. Additionally, our finding also indicates that 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 people's interests in advance.

	M1 (Like)	
Predictors	*Log Odds*	*p*
(Intercept)	-3.40	0.243
Replace	-2.46	**0.048**
Emphasize	-0.47	0.536
Belief	0.79	**0.001**
Visit_Twitter [2-5 times a day]	0.60	0.568
Visit_Twitter [5-10 times a day]	0.45	0.634
Visit_Twitter [Not everyday]	-12.17	0.998
Visit_Twitter [Once a day]	2.26	0.151
Sharing [Daily]	-0.98	0.709
Sharing [Every few months]	-0.95	0.719
Sharing [Every few weeks]	-1.63	0.574
Sharing [Multiple times a day]	-17.09	0.993
Sharing [Weekly]	-0.38	0.882
Twitter_Hours [3-5 Hours]	0.75	0.428
Twitter_Hours [A Less than 1 hour]	-1.14	0.672
Twitter_Hours [More than 5 Hours]	-0.42	0.632
Observations	99	
Null Deviance	87.58	
Residual Deviance	57.59	
McFadden R2	0.34	

Table 8. Results from Model 1 for Like as the predicted variable.

	M2 (Like)	
Predictors	*Log Odds*	*p*
(Intercept)	-24.58	0.997
Replace	-0.004	0.998
Emphasize	3.65	**0.010**
Belief	1.14	**0.002**
Visit_Twitter [2-5 times a day]	0.83	0.488
Visit_Twitter [5-10 times a day]	-1.42	0.262
Visit_Twitter [Not everyday]	3.45	1.000
Visit_Twitter [Once a day]	-0.19	0.917
Sharing [Daily]	16.07	0.998
Sharing [Every few months]	15.81	0.998
Sharing [Every few weeks]	14.81	0.998
Sharing [Multiple times a day]	1.31	1.000
Sharing [Weekly]	16.83	0.998
Twitter_Hours [3-5 Hours]	2.98	**0.045**
Twitter_Hours [A Less than 1 hour]	-14.39	0.997
Twitter_Hours [More than 5 Hours]	0.51	0.682
Observations	99	
Null Deviance	80.68	
Residual Deviance	40.021	
McFadden R2	0.50	

Table 9. Results from Model 2 for Like as the predicted variable.

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 in Model M1

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 in Model M2

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 communication. Our work provides empirical evidence to show that information containing non-verbal such as emojis lead to more engagement on average (more likes and retweets). This suggests that future studies should account for the effect of emojis 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. In addition, we present empirical evidence that certain emojis are connected with true news while others are associated with fake news. This suggests that emojis serve distinct functions within the same social realm. Future study must take into account the 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). We also present experimental data demonstrating the functional importance of emojis in text. Nonverbal communication allows for a clearer expression of emotion than text alone. In different circumstances, the probability of emojis transmitting their functional role varies.

6.2 Practical Implications

Our findings have substantial implications for practitioners as well. Distributors of fake news consistently strive to spread disinformation or do harm to society. This research advises organizations to examine harmful email patterns to determine if certain nonverbal indicators are routinely employed, so that employees may be alert. Examining these emojis that circulate or are part of fake news within an organization may also aid in preventing the spread of misinformation. They can utilize the emojis discovered in this study as a baseline, but they may additionally include context-specific emojis. To identify fake news on their platforms, social media companies such as Twitter may also analyze emojis to determine if anything that contains emojis is gaining popularity.

7. Conclusion

In this study, we examined the impact of nonverbal communication on the dissemination of information. We gathered data from a fact-checking website and analyzed tweets by splitting them into those with and without emojis. We found that news using non-verbal symbols leads to more engagement than tweets without emojis. In addition, we discovered that certain emojis were more frequently connected with real information than with fake news. We also examined the role emojis play in the dissemination of information. We ran an experiment to investigate the effect of a non-verbal token substituting a verbal token, with the non-verbal token emphasizing text as opposed to information with no non-verbal token. In this study, we found that the functional role of nonverbal communication influenced fake news but had no effect on genuine information. When emojis emphasize text, they are liked more, however when they substitute text, they are liked less compared to content that does not contain emojis. Our study has theoretical and practical implications.

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Appendix A

Figure 1A. 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 2A. True information. Same conditions described in Figure 1A.

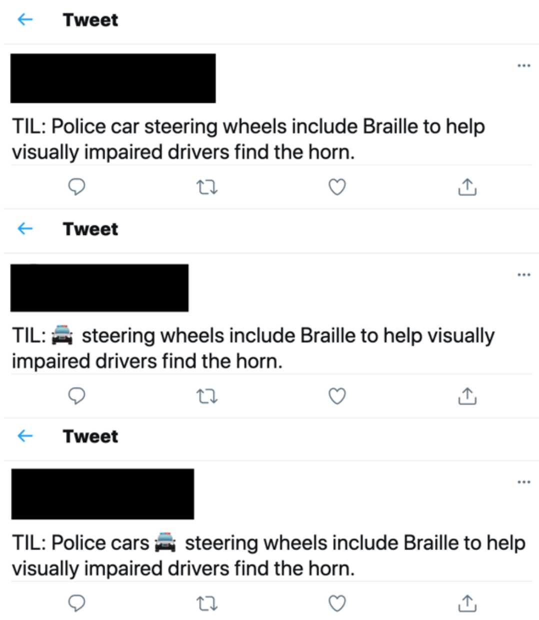

Figure 3A. Fake Information. Same conditions described in Figure 1A.

Figure 4A. Fake Information. Same conditions described in Figure 1A.