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Unmasking an Infodemic: What Characteristics are Fuelling Misinformation on Social Media?

Abstract

The COVID-19 pandemic has created an infodemic, flooding various media channels. While much research has focused on detecting false information or assessing the severity of the problem, little attention has been given to the role of message and source characteristics in information dissemination. To address this gap, we developed a research model based on the Undeutsch hypothesis, four-factor theory, and source credibility theory. We analysed a pre-defined dataset involving fake and true tweets from Twitter. We examined their messages and source characteristics through descriptive statistics, negative binomial regression, and multi-group analyses. Our findings revealed significant differences in the dissemination of false and true tweets. By understanding the impact of message and source characteristics on the spread of misinformation, we can create a more informed and trustworthy information ecosystem during times of crisis. These results have crucial implications for practitioners, providing insight into developing effective strategies to combat COVID-19 misinformation.

Keywords: COVID-19, misinformation, infodemic, information dissemination, Twitter

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1. Introduction

In today's rapidly evolving digital landscape, the importance of data cannot be overstated. In our current era, characterized by abundant information, we are surrounded by vast data that fuels the digital world (Saura et al., 2022). Data is the backbone of modern society, driving innovation and powering technological advancements across industries. With its ability to provide insights, reveal patterns, and identify trends, data has become an invaluable asset for decision making and problem solving. From healthcare and finance to marketing and education, data applications are endless, potentially revolutionizing industries and transforming society.

Social networks have become one of the most critical data sources in today's digital age (Zhang & Ghorbani, 2020). With billions of users worldwide, social networks offer unprecedented insight into human behaviour, preferences, and opinions. From Facebook and Twitter to Instagram and TikTok, social networks provide a vast treasure trove of data that can be mined for valuable insights. On the other hand, the increased utilization of social networks has led to an unparalleled chance to disseminate inaccurate information (Fernández-Torres et al., 2021). There can be various reasons behind sharing misinformation. For example, misinformation can trigger strong emotions like fear, anger, or anxiety. When people feel emotionally aroused, they may be more likely to share information without verifying its accuracy or credibility. They might also want to provoke an emotional response from others or to gain attention and validation from their social media followers. Another reason can be confirmation bias (Nickerson, 1998). When individuals come across information that supports their beliefs, attitudes, and values, they may share it without verifying its authenticity. Also, people often feel pressured to conform to the beliefs and opinions of their social circle, family, or community (Hogg, 2016). This pressure can lead individuals to share misinformation, especially if they fear being excluded by their social group. Additionally, individuals may intentionally share misinformation to reinforce their worldview or deceive others due to the motivated reasoning (Kunda, 1990).

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During the COVID-19 pandemic, people spent many hours on social networking sites due to lockdowns and quarantines (Alam et al., 2021). The virus's novelty and unprecedented pandemic created a climate of uncertainty and fear. This climate led people to seek information to understand and protect themselves. However, with the overwhelming amount of online information, it could be challenging to differentiate between credible and unreliable sources due to the lack of credible sources and clear and consistent messaging from authorities and experts early in the pandemic (Naeem & Bhatti, 2020). As a result, it created confusion among the public and left a gap filled by misinformation. Professionals and policymakers should take a more proactive approach to educating the public about the traits of misinformation that contribute to its widespread dissemination in society. (Song et al., 2023). However, the rapid spread of the virus and the fast pace of information dissemination created a sense of urgency among users to share information, often without verifying its accuracy or reliability. So, individuals ended up sharing information that they perceived as accurate but was, in reality, false. All these problems have led to an infodemic because of an overabundance of accurate and inaccurate information that is often difficult to verify or even understand. Director-General of the World Health Organization, Tedros Adhanom Ghebreyesus, emphasized the challenging problem we faced and stated, "We are not just fighting an epidemic; we are fighting an infodemic" (*Munich Security Conference*, n.d.). Evidently, this infodemic has caused confusion, provoked hatred, and promoted unverified cures, social panic, and even mass poisoning (Ding et al., 2020; van der Linden et al., 2020).

Researchers have focused on information spread by analysing comprehensive sources to fight this infodemic. For example, some studies collected data by distributing surveys to focus on false content sharing on social networking sites. Fernández-Torres et al. (2021) analysed the proliferation of COVID-19-related false news and its impacts on public opinion in Spain. Their results indicated that people wanted to follow COVID-19-related information. Nevertheless, the lack of media credibility and reliability was the main problem. However, Pennycook et al. (2020) revealed that individuals also failed to consider whether the content was false while deciding what to share. Their survey results highlighted that one of the simplest ways could be only nudging people to think about the accuracy of content before sharing it. Apuke and Omar (2020a, 2020b) also suggested intervention strategies like nudging people to doubt before sharing content. Their studies found that tie strength, perceived herd, social networking dependency, information-seeking, parasocial interactions, altruism, instant news sharing, socialization, and self-promotion could be underlying predictors related to false content sharing. In contrast, Raj and Goswami (2020) believed that self-regulation could be insufficient to prevent the spreading of false content. In this regard, social media literacy should be built, and a national policy and regulatory body could be necessary to control the spread of misinformation.

There were also studies exploring different aspects of the infodemic surrounding COVID-19 using social media data. (K. Chen et al., 2021) collected 547 pieces of misinformation from one of China's social media sites during the pandemic. They classified misinformation into categories based on their content and thematic status. They presented descriptive statistics, the most-mentioned information, and a development timeline. The results showed that preventative and therapeutic methods were mostly mentioned. Cultural and social beliefs had an effect on the perception and propaganda of misinformation. (Song et al., 2023) identified message features of misinformation by investigating the impact of novelty and efficacy of protective actions conveyed in misinformation on the intention to share it on social media. They also analysed the mechanisms behind the novelty and efficacy. In an online experiment of 1,012 adults in South Korea in 2020, they highlighted the negative impact of novelty and the positive effect of efficacy on misinformation-sharing intention.

Kouzy et al. (2020) identified the extent of misinformation by collecting COVID-19-related hashtags and keywords. They distinguished 153 tweets out of 673, including misinformation regarding the COVID-19 pandemic. Tweets from unverified Twitter accounts comprised more misinformation than verified ones. Pulido et al. (2020) revealed that although false information was tweeted more, it was less retweeted than science-based evidence or fact-checking tweets. Huang and Carley (2020) also found that tweets involving fake news links were more likely to be retweeted than real and regular tweets, but only in the source country. They also found that regular users tended to spread fake news and disinformation more than government officials and individual reporters did. Sharma et al. (2020) provided analysis of social media discourse about COVID-19 on Twitter through analysis of misinformation claims identified using information about low-quality news websites from fact-checking sources and analysis of sentiments, topics, and emerging trends in the online discourse. They presented a dashboard analysis and daily updated list of identified misinformation claims during the pandemic.

Gruzd and Mai (2020) examined the effect of conservative politicians and activists on conspiracy dissemination. The study revealed that those politicians and activists started the fire that led to conspiracy dissemination. Finally, Ferrara (2020) and Yang et al. (2020) investigated bots' role in spreading low-credibility information. While Ferrara (2020) used machine learning and statistical analysis to detect bots, Yang et al. (2020) analysed the content and characteristics of tweets to identify the role of bots. Yang et al. (2020) revealed that social bots were involved in posting and amplifying low-credibility information, although most of the volume was generated by likely humans. Ferrara (2020) highlighted that bots could be used for good, e.g., to bring to light issues that would otherwise get censored or ignored. Conversely, bots could be abused to distort online narratives to promote political ideologies.

Furthermore, some studies concentrated on detecting false content by developing technical or computational tools. Nashif (2021) developed an analysis to locate where misinformation spreads on Twitter and identify reliable tweets. Abdelminaam et al. (2021) built a computerized system to identify false content using deep learning techniques. Gupta et al. (2021) used natural language process techniques to build a model. In another study, Alsudias & Rayson (2020) used three machine-learning algorithms to classify rumor-related tweets. Al-Rakhami and Al-Amri (2020) used machine learning algorithms and a dataset assessed and labelled by human annotators to extract user and tweet-related features. In the CONSTRAINT workshop at AAAI 2021, researchers developed models using computational tools to detect fake news with a dataset including COVID-19-related posts from social networks (Bang et al., 2021; Patwa et al., 2021; Shifath et al., 2021).

However, research on the subject has been mostly restricted to detecting deception, fake news, misinformation, and bots on social media. Some studies only emphasized the need for practices to limit the spread of false information by presenting its severe consequences. Not only does this study focus on misinformation as previous studies, but it also compares true and false information to find the differences in message and source characteristics for the development of effective strategies to combat the spread of misinformation. It explores the message and source characteristics of tweets to provide insights into information dissemination mechanisms. We selected Twitter because it has played a significant role in shaping public opinion and influencing behaviour related to the COVID-19 pandemic. It has become a platform for experts, public health officials, and politicians to provide updates, guidance, and recommendations about the pandemic. Individuals have used Twitter to share personal experiences and emotions about the pandemic, as well as to connect with others and seek social support. The study proposes a research model based on the Undeutsch hypothesis, four-factor theory, and source credibility theory (Birnbaum & Mellers, 1983; Undeutsch, 1967; Zuckerman et al., 1981). Ultimately, it seeks answers to two research questions: (1) *What specific message and source characteristics play a role in information dissemination*? (2) *How do message and source characteristics vary in their roles when disseminating true and false information?*

2. Research Model and Hypotheses

Forensic psychologists in Germany have formulated qualitative criteria for evaluating the content of statements and determining their validity. The assessment of truthfulness relies on the Undeutsch hypothesis, which posits that statements stemming from the recollection of a personally experienced event will exhibit qualitative distinctions from statements rooted in imagination or suggestion (Wojciechowski, 2014). Since the Undeutsch hypothesis is initially

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designed for assessing the validity of statements derived from memory of self-experienced events, we adapted the criteria to suit the context of online communication and social media. The Undeutsch Hypothesis considers that real statements and claims are more unique and specific than false statements. It is reasonable to expect that legitimate messages on the same subject will possess certain similarities to one another and will be different from fake messages in terms of their content and structure (Tsai, 2023). In this sense, false information potentially differs in writing style from true information (Undeutsch, 1967). As a result, we identified key message characteristics that may differentiate authentic information from fabricated content in the digital space inspired by the Undeutsch hypothesis and existing literature (AlRubaian et al., 2015; Alrubaian et al., 2017; Aphiwongsophon & Chongstitvatana, 2018; Castillo et al., 2013; Indu & Thampi, 2019; Jin et al., 2017; Ma et al., 2015; Sahana, et al., 2015; Varol et al., 2017; Wu et al., 2017).

As Figure 1 shows, we investigated the existence of a question mark (?), an exclamation mark (!), an ellipsis (…), the number of words in capital letters, and whether the content involved only uppercase letters. Using a question mark can imply uncertainty or doubt, creating the impression that the writer is simply asking a question, not making a definitive statement. Using an exclamation mark can convey a sense of urgency or excitement, making the information seem more significant than it actually is. Using an ellipsis can create a sense of ambiguity or mystery, making the information seem more exciting or intriguing than it is. Text written entirely in capital letters can create a sense of urgency and alarm the reader, leading them to believe that the information is critical or urgent, even if it is untrue. Words in capital letters can be used to emphasize certain phrases or words to make them stand out and appear more important than they actually are.

We also added the existence of media (i.e., video, image, gif), hyperlinks, emoticons, and platform-specific features to this group. Including those features can attract public awareness, increase engagement, and lead to subsequent dissemination of misinformation (Orellana-Rodriguez et al., 2016). Messages look transparent and informative when they include

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eyewitness evidence, such as a video or image (Bondielli & Marcelloni, 2019). Individuals or groups can hijack hashtags about a particular event or topic to spread false information. Even bots or fake accounts may use hashtags and mentions to amplify false information and create the illusion of popular support for a particular narrative. Mentions can be used to give credibility to false information by tagging influential individuals or organizations in the post. Manipulated videos that include deep fakes or other techniques can deceive viewers and contribute to the spread of false information. A user might reference a false tweet to add to its credibility and increase its visibility.

Zuckerman et al. (1981) proposed the influential four-factor theory of deception. It postulates that deception involves (a) generalized arousal, (b) anxiety, guilt, and other emotions accompanying deception, (c) cognitive components, and (d) liars' attempts to control verbal and non-verbal cues to appear honest (Walczyk et al., 2013). While these authors suggest that lying may impose a higher cognitive load than truth-telling, leading to indicators such as prolonged response times and increased pupil dilation, the theory does not provide a comprehensive explanation of the cognitive mechanisms involved in deception. Nevertheless, it underscores deception's intricate and multifaceted nature, acknowledging various behaviours, including emotional cues, as potential indicators. Misinformation is frequently framed using emotional language and appeals to elicit emotional reactions, contributing significantly to its widespread dissemination and virality (S. Chen et al., 2023).We implemented a sentiment analysis, extending beyond textual content to incorporate both verbal and non-verbal cues. This comprehensive approach includes evaluating sentiment scores not only for the explicit text but also for the non-physical aspects of the messages, providing a more nuanced understanding of emotional expression in our analysis. For example, misinformation might reflect strong positive or negative feelings in the content's body to appeal to the reader's feelings rather than rational thinking (Zhang & Ghorbani, 2020). Misleading information about the virus or vaccines may be presented to evoke fear, anger, or distrust toward public health officials, leading to the spread of misinformation. So, we hypothesized that:

H1: Message characteristics impact information dissemination.

Additionally, source characteristics might contribute to misinformation dissemination. Defining and assessing the source becomes especially challenging when information circulates through social media, as any user can act as a content publisher (S. Chen et al., 2023). The source credibility theory explains how people perceive information sources' credibility based on the source's social image and status (Birnbaum & Mellers, 1983). According to the theory, people tend to give more weight to information from credible and trustworthy sources, such as experts, authorities, and people with high social status, even if the information is incorrect or misleading. Conversely, information from sources perceived as untrustworthy or low status is often discounted or ignored. One of the most common social cues is the number of followers and followings (Castillo et al., 2013). Twitter influencers, who have many followers and followings, might be seen as more credible or authoritative, get users' notice, and lead them to talk about a particular person, event, or thing (Community, 2016). As a result, more people view and respond to tweets, and information dissemination increases (Lehmann et al., 2013). Furthermore, users' total number of tweets indicates their activity level and influence on Twitter. Users with many total tweets may have built a certain level of credibility or authority, making their false information more convincing to their followers (Orellana-Rodriguez et al., 2016). Moreover, Twitter gives a blue verified badge for authentic, remarkable, and active accounts (Twitter Help Center, n.d.). Verified accounts are usually associated with credible sources, and their tweets are more likely to be seen and shared by other users. This means that verified accounts can potentially have a more significant impact in spreading misinformation if they happen to share false information. After going through previous literature, we grouped these characteristics as source characteristics (see Figure 1) and hypothesized that:

H2: Source characteristics impact information dissemination.

Incorporating the mediating impact of content type, true and false information, into our research model, we scrutinized and differentiated between the characteristics behind false information dissemination. By examining the disparities, we could pinpoint the specific message and source characteristics used to manipulate and distort information and understand the underlying mechanisms involved in spreading misinformation. Thus, we hypothesized that:

H3: Content type moderates the impact of message characteristics on information dissemination.

H4: Content type moderates the impact of source characteristics on information dissemination.

We used two widely accepted measures, retweet count and favourite/like count, to estimate the dissemination of information on Twitter. Retweet count represents the number of times a tweet is shared or reposted by other users, while favourite/like count reflects the number of times a tweet is marked as a favourite or liked by users. These two measures are indicators of information dissemination, because retweeted and favoured posts are shown on Twitter users' timelines.

3. Methodology

We used a pre-defined dataset, including tweets about the pandemic (Memon & Carley, 2020). The researchers used Twitter search API. First, they collected 4,573 tweets with specific keywords on March 29, 2020, June 15, 2020, and June 24, 2020 (see Appendix A). Then, they investigated tweets and annotated them, identifying 17 categories (see Appendix B). We selected this dataset because of its diversity in the range of topics covered. Also, it does not employ automated annotations using semi-supervised or transfer learning methods not designed for misinformation.

The dataset included only tweet IDs, the date the tweet was created, and its annotation. We sampled tweet IDs based on their annotations to create two datasets to compare false and true content. We chose tweet IDs from similar categories to make a homogenous dataset and reliable comparison. While false tweets included tweet IDs annotated as "fake cure," "fake treatment," "false fact or prevention," and "false public health response," true tweet IDs consisted of tweets annotated as "true prevention," "true public health response," and "true treatment." We ended up with 499 false and 338 tweet IDs.

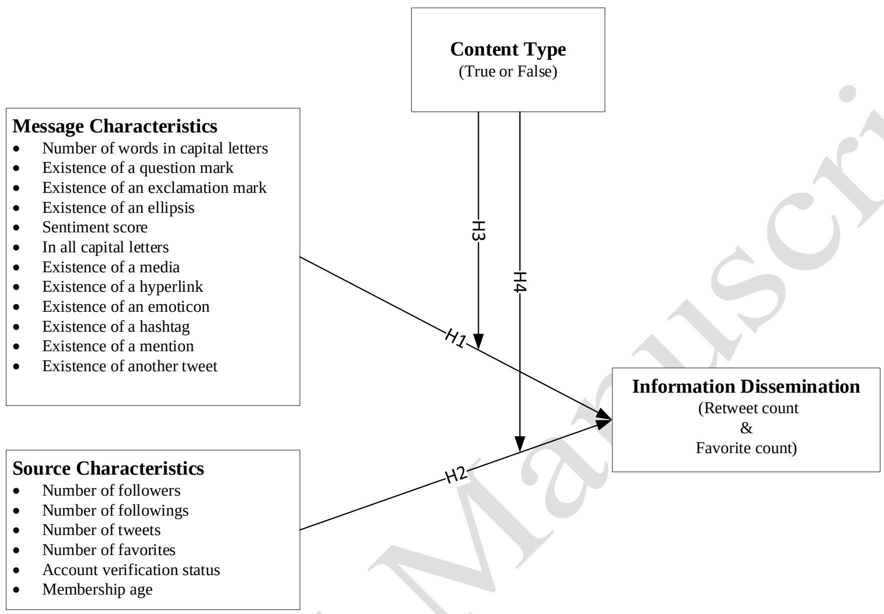

Figure 1. Research model

We used Twarc, a command-line tool, and Python library to extract full tweet texts and source characteristics (Documenting the Now, n.d.). Twarc collected 378 false tweets out of 499 and 313 true tweets out of 338 because of deleted tweets and suspended and private accounts. Twarc fetched the full text, tweet link, sources' number of followers, followings, tweets, favourites, the date the account was created, and account verification status. It also fetched the number of times a tweet was retweeted and favoured. However, all the results were in a semi-structured data format (JSON Lines file). Thus, we structured data for further analysis. We calculated membership age in years by subtracting the year we collected data from the year the account was created.

To extract message characteristics, we used QDA Miner. For each tweet, we identified the existence of a question mark, exclamation mark, ellipsis, emoticon, hashtag, mention, tweets including words only in capital letters, and the number of words in capital letters. To find the existence of media, we visited each tweet link. Next, we used SentiStrength to extract sentiment scores. It calculated positive and negative sentiment scores based on a polarity between -5 and 5 (Thelwall et al., 2010). In the last stage, we gathered all these extracted characteristics (see Table 1).

To answer the research questions, we analysed the descriptive statistics and compared the characteristics across two datasets. Then, we combined two datasets, applied negative binomial regression analysis (NBREG) on Stata 16.1, and assessed the mediating impact of content type to answer the second research question. NBREG allowed us to make inferences about the importance and magnitude of the main effects of the message and source characteristics. Lastly, we applied a multi-group analysis with WarpPLS 7.0 to make a pair-wise comparison across true and false content types. A critical ratio was calculated based on a pooled standard (Kock, 2014). We got the pair-wise comparisons, T-values, and their significance level.

Table 1. Characteristics in the dataset

Features	Description
Independents	
Message Characteristics	
Words in capital letters	The number of words in capital letters
Question mark	Whether a question mark is included (1: Yes, 0: No)
Exclamation mark	Whether an exclamation mark is included (1: Yes, 0: No)
Ellipsis	Whether an ellipsis is included (1: Yes, 0: No)
In all capital letters	Whether all words are in capital letters (1: Yes, 0: No)
Sentiment score	The calculated positive and negative sentiment scores
Media (image, video, or gif)	Whether media is included (1: Yes, 0: No)
Hyperlink	Whether a link is included (1: Yes, 0: No)
Emoticon	Whether an emoticon is included (1: Yes, 0: No)
Mention	Whether a mention is included (1: Yes, 0: No)
Hashtag	Whether a hashtag is included (1: Yes, 0: No)
Another tweet	Whether another tweet is included (1: Yes, 0: No)
Source Characteristics	
Followers	The number of followers of a given account
Followings	The number of followings by a given account
Tweets	The number of tweets posted by a given account

Favourites	The number of tweets favourited by a given account
Membership age	The calculated membership age of an account in years
Verification status	Whether an account is verified (1: Yes, 0: No)
Dependents	
Retweet count	The number of times a tweet is retweeted
Favourite count	The number of times a tweet is favoured

4. Results

4.1. Descriptive Statistics

According to Table 2, 24.60% of tweets were retweeted, and 49.21% were favoured in the false tweets dataset. On the other hand, 45.37% of tweets were retweeted, and 62.30% were favoured in the true tweets dataset. Additionally, on average, fake tweets were retweeted 1.26 times and favoured 4.85 times. On the other hand, true tweets were retweeted 16.80 times and favoured 89.05 times.

According to Table 3, false tweets included more question marks, exclamation marks, ellipses, capital letters, and other tweets than true ones. True tweets contained more only capital letters, media, hyperlinks, emoticons, mentions, and hashtags than false tweets. False tweets were more positive and negative than true based on sentiment scores. 26.46% of the sources were verified accounts in the true tweets dataset and 2.91% in the false tweets dataset. Sources in the true tweets dataset were more experienced than users in the false tweets dataset. They had more followers, followings, and tweets than false tweet creators did. On the other hand, false tweet sources favoured or liked more other tweets than true tweet sources did.

Table 2. Descriptive statistics of dependents

	Frequency		**Percentage**		**Mean**		**Standard Deviation**	
	False (N=378)	True (N=313)	False (N=378)	True (N=313)	False (N=378)	True (N=313)	False (N=378)	True (N=313)
Retweeted	93	142	24.60	45.37	-	-	-	-
Favourited	186	195	49.21	62.30	-	-	-	-
Retweet count	-	-	-	-	1.26	16.80	5.78	109.71
Favourite count	-	-	-	-	4.85	89.05	24.69	773.17

Table 3. Descriptive statistics of independents

Characteristics	**Frequency**		**Percentage**		**Mean**		**Standard Deviation**	
	False (N=378)	True (N=313)	False (N=378)	True (N=313)	False (N=378)	True (N=313)	False (N=378)	True (N=313)
Message Characteristics								
Number of words in capital letters	-	-	-	-	0.49	0.19	2.15	2.11
Question mark	41	23	10.85	7.35	-	-	-	-
Exclamation mark	54	21	14.29	6.71	-	-	-	-
Ellipsis	39	13	10.32	4.15	-	-	-	-
In all capital letters	6	6	1.59	1.92	-	-	-	-
Sentiment score	-	-	-	-	-	-	-	-
Positive sentiment score	-	-	-	-	1.51	1.49	0.68	0.66
Negative sentiment score	-	-	-	-	-1.81	-1.77	0.94	0.88
Media	79	97	20.90	30.99	-	-	-	-
Link	235	253	62.17	80.83	-	-	-	-
Emoticon	31	36	8.20	11.50	-	-	-	-
Mention	47	52	12.43	16.61	-	-	-	-
Hashtag	135	150	35.71	47.92	-	-	-	-
Another tweet	38	18	10.05	5.75	-	-	-	-
Source Characteristics								
Followers	-	-	-	-	48,363.52	59,4320.19	70,2082.73	500,6819.87
Followings	-	-	-	-	1,836.08	1,875.88	5,535.03	4,195.15
Tweets	-	-	-	-	51,331.09	56,282.66	137,653.11	112,237.38
Favourites	-	-	-	-	20,283.57	17,011.61	49,777.81	48,647.72
Membership age	-	-	-	-	6.62	9.19	4.08	3.89
Verification status	11	100	2.91	26.46	-	-	-	-

4.2. Hypothesis Testing

NBREG is suitable if the dependent variable includes over-dispersed count data (Hilbe, 2011). We tested for overdispersion and did a 1-tailed test of H0: $\alpha=0$ for two models, including retweet count and favourite count. Table 4 shows the likelihood-ratio test of alpha when it is equal to 0. The alpha differed significantly from 0 for both models. We compared Akaike's information criterion (AIC) and Bayesian information criterion (BIC) (Burnham & Anderson, 2004) by running both Poisson and NBREG Analyses for a model selection. Table 5 shows that the model became more desirable as AIC and BIC decreased (Lindsey & Sheather, 2015). Therefore, we concluded that NBREG was an appropriate analysis to apply.

Table 4. Likelihood-ratio test of alpha=0

Dependent	**Chibar2 (01)**	**Prob >=chibar2**

Retweet Count	5,412.88	0.000
Favourite Count	25,000	0.000

Table 5. Likelihood-ratio test with AIC and BIC

Model	N	ll(null)	ll(model)	df	AIC	BIC
Poisson – Retweet Count	691	-20867.03	-3721.041	40	7522.082	7703.607
NBREG – Retweet Count	691	-1178.166	-1014.602	41	*2111.204*	*2297.268*
Poisson – Favourite Count	691	-126511.93	-12854.93	39	27787.85	27964.84
NBREG – Favourite Count	691	-1848.452	-1600.67	41	*3283.34*	*3469.404*

Tables 6 and 7 include the main and interaction effects on retweets and favourite counts. Both tables contain fitted model statistics, beta coefficients, standard errors, t-values, incident rate ratios (IRR), and percentage change in the expected count. The beta coefficients imply how much a one-unit increase in each independent variable increases the μ (Williams, 2021). However, it does not provide valuable insights, so we exponentiated the coefficients to calculate IRRs. IRR tells us how changes in a characteristic impact the rate at which tweets are retweeted and favoured.

According to Table 6, only positive and negative sentiment scores had significant negative impacts on message characteristics. The percentage column indicated that by increasing the positive sentiment score by one point, the retweet count would be expected to decrease by 33.60%. Each additional negative sentiment score reduced the retweet count by 34.20%. A tweet with a hyperlink was 50% less retweeted than one without a hyperlink. Source characteristics had more significant effects on retweet count than message characteristics. Each additional year of membership age increased the retweet count by 12.10%. A tweet posted by a verified account was more retweeted than a tweet posted by an unverified account. Although the number of followings and followers were minimal, they affected the retweet count. Only the interaction of membership age with content type significantly impacted the retweet count. A true tweet posted by a more experienced user (with additional membership age) was 13.90% less retweeted than a false tweet posted by a more experienced source.

According to Table 7, the number of words in capital letters and tweets, including only capital letters, significantly negatively affected the favourite count. Each additional word in capital letters in a tweet decreased the favourite count by 13.40%. A tweet including only capital letters compared to a tweet not including only capital letters was expected to be 97.80% less favoured. The interaction effect implied that a true tweet with only capital letters was more favoured than a false tweet with only capital letters. A tweet including media compared to a tweet without media was expected to be 100.80% more favoured. A tweet with a hashtag was 58.50% less favoured than one with no hashtag. A tweet including a hyperlink compared to a tweet without a hyperlink was 65.20% less favoured. A source's number of tweets and favourites had a small significant impact. Membership age and verification status played a crucial role. Each additional membership year increased the favourite count by 7.50%.

The results showed that message and source characteristics impacted information dissemination. Furthermore, the effects of message characteristics (specifically in all capital letters) and source characteristics (precisely membership age) depended on the content type. Table 8 shows the multi-group analysis results. Although message characteristics did not play an important role in distinguishing true and false tweets, source credibility features moderated information dissemination.

Table 6. Negative Binomial Regression Results on Retweet Count

Retweet Count	**Coef.**	**St. Err.**	**t-value**	**IRR**	**%**
Main Effects					
Content type[b]	*1.774***	0.862	2.06	5.894	489.40
Message Characteristics					

Positive sentiment score[c]	-0.409*	0.242	-1.69	0.664	-33.60
Negative sentiment score[c]	-0.419***	0.149	-2.80	0.658	-34.20
Words in capital letters[c]	-0.067	0.075	-0.88	0.935	-6.50
Question mark[a]	-.0458	0.475	-0.96	0.633	-36.70
Exclamation mark[a]	0.535	0.427	1.25	1.708	70.80
Ellipsis[a]	-.0491	0.521	-0.94	0.612	-38.80
In all capital letters[a]	-2.018	1.461	-1.38	0.133	-86.70
Media[a]	0.428	0.425	1.01	1.534	53.40
Another tweet[a]	-0.37	0.528	-0.70	0.690	-31.00
Hashtag[a]	-0.145	0.301	-0.48	0.865	-13.50
Emoticon[a]	0.098	0.525	0.19	1.103	10.30
Hyperlink[a]	-.693**	0.331	-2.09	0.500	-50.00
Mention[a]	-0.274	0.471	-0.58	0.760	-24.00
Source Characteristics					
Followers[c]	0.000	0.000	0.66	1.000	0.00
Followings[c]	0.000**	0.000	2.35	1.000	0.00
Membership age[c]	0.114***	0.039	2.97	1.121	12.10
Favourite[s]	0.000	0.000	0.09	1.000	0.00
Verification status[a]	2.192***	0.825	2.66	8.953	795.30
Tweets[c]	0.000*	0.000	-1.89	1.000	0.00
Interaction Effects					
Message Characteristics					
Content type # positive sentiment score	0.338	0.340	1.00	1.403	40.30
Content type # negative sentiment score	0.321	0.222	1.45	1.379	37.90
Content type # words in capital letters	-0.363	0.352	-1.03	0.696	-30.40
Content type # question mark	0.469	0.733	0.64	1.598	59.80
Content type # exclamation mark	-0.344	0.746	-0.46	0.709	-29.10
Content type # ellipsis	-0.727	0.924	-0.79	0.483	-51.70
Content type # in all capital letters	1.025	1.829	0.56	2.786	178.60
Content type # media	0.235	0.582	0.40	1.265	26.50
Content type # another tweet	0.816	0.912	0.89	2.262	126.20
Content type # hashtag	-0.584	0.473	-1.23	0.558	-44.20
Content type # emoticon	0.515	0.704	0.73	1.673	67.30
Content type # hyperlink	-0.616	0.533	-1.16	0.540	-46.00
Content type # mention	0.656	0.650	1.01	1.927	92.70
Source Characteristics					
Content type # followers	0.000	0.000	-0.30	1.000	0.00
Content type # followings	0.000	0.000	0.22	1.000	0.00
Content type # membership age	-0.15**	0.063	-2.39	0.861	-13.90
Content type # favourites	0.000	0.000	0.73	1.000	0.00
Content type # verification status	1.021	0.894	1.14	2.776	177.60
Content type # tweets	0.000	0.000	0.87	1.000	0.00
Constant	-0.784*	0.436	-1.80		
lnalpha	1.472	0.090			

Mean dependent var	8.301	SD dependent var	74.417
Pseudo r-squared	0.139	Number of obs	691
Chi-square	327.127	Prob > chi2	0.000

**** p<.01, ** p<.05, * p<.1*
a: categorical variable (1: Yes/Existing 0: No/Not Existing, base=0)
b: categorical variable (1: True Tweet, 0: False Tweet, base=0)
c: continuous variable

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Table 7. Negative Binomial Regression Results on Favourite Count

Favourite Count	Coef.	St. Err.	t-value	IRR	%
Main Effects					
Content type[b]	0.375	0.811	0.46	1.455	45.50
Message Characteristics					
Positive sentiment score[c]	-0.053	0.201	-0.26	0.949	-5.10
Negative sentiment score[c]	-0.192	0.134	-1.43	0.826	-17.40
Words in capital letters[c]	*-0.144***	0.071	-2.03	0.866	-13.40
Question mark[a]	-0.587	0.382	-1.54	0.556	-44.40
Exclamation mark[a]	0.138	0.374	0.37	1.148	14.80
Ellipsis[a]	-0.192	0.422	-0.45	0.825	-17.50
In all capital letters[a]	*-3.817***	1.534	-2.49	0.022	-97.80
Media[a]	*0.697**	0.364	1.91	2.008	100.80
Another tweet[a]	-0.295	0.437	-0.67	0.744	-25.60
Hashtag[a]	*-0.881****	0.266	-3.31	0.415	-58.50
Emoticon[a]	0.251	0.448	0.56	1.286	28.60
Hyperlink[a]	*-1.055****	0.28	-3.77	0.348	-65.20
Mention[a]	-0.293	0.394	-0.74	0.746	-25.40
Source Characteristics					
Followers[c]	0.000	0.000	0.61	1.000	0.00
Followings[c]	0.000	0.000	1.59	1.000	0.00
Membership age[c]	*0.073***	0.034	2.16	1.075	7.50
Favourite[s]	0.000*	0.000	1.84	1.000	0.00
Verification status[a]	*2.806****	0.774	3.62	16.550	1555.00
Tweets[c]	*0.000****	0.000	-2.82	1.000	0.00
Interaction Effects					
Message Characteristics					
Content type # positive sentiment score	0.433	0.304	1.43	1.542	54.20
Content type # negative sentiment score	0.136	0.201	0.67	1.145	14.50
Content type # words in capital letters	0.054	0.090	0.60	1.055	5.50
Content type # question mark	0.848	0.614	1.38	2.335	133.50
Content type # exclamation mark	0.037	0.661	0.06	1.038	3.80
Content type # ellipsis	-0.840	0.790	-1.06	0.432	-56.80
Content type # in all capital letters	*3.196**	1.794	1.78	24.435	2343.50
Content type # media	0.405	0.498	0.81	1.500	50.00
Content type # another tweet	0.428	0.793	0.54	1.534	53.40
Content type # hashtag	0.333	0.421	0.79	1.395	39.50
Content type # emoticon	-0.051	0.607	-0.08	0.950	-5.00
Content type # hyperlink	-0.734	0.464	-1.58	0.480	-52.00
Content type # mention	0.421	0.566	0.74	1.524	52.40
Source Characteristics					
Content type # followers	0.00	0.000	-0.38	1.000	0.00
Content type # followings	0.00	0.000	0.26	1.000	0.00
Content type # membership age	-0.085	0.056	-1.53	0.919	-8.10
Content type # favourites	0.00	0.000	-0.10	1.000	0.00
Content type # verification status	0.956	0.842	1.14	2.602	160.20
Content type # tweets	0.00	0.000	0.68	1.000	0.00
Constant	*1.212****	0.359	3.38		
lnalpha	1.336	0.065			
Mean dependent var		42.993	SD dependent var		522.750
Pseudo r-squared		0.134	Number of obs		691
Chi-square		495.564	Prob > chi2		0.000

**** p<.01, ** p<.05, * p<.1*
a: categorical variable (1: Yes/Existing 0: No/Not Existing, base=0)
b: categorical variable (1: True Tweet, 0: False Tweet, base=0)
c: continuous variable

Table 8. Multi-group analysis

Pairwise Comparison (True/False Tweet)		
Characteristics	**T-Ratios**	
	Retweet Count	Favourite Count
Message Characteristics		
Number of words in capital letters	0.160	0.210
Question mark	0.282	0.479
Exclamation mark	0.158	0.214
Ellipsis	0.315	0.212
In all capital letters	0.103	0.029
Positive sentiment score	0.958	0.537
Negative sentiment score	0.635	2.620***
Media	0.540	0.266
Link	0.527	0.995
Emoticon	0.615	0.968
Mention	0.060	0.053
Hashtag	0.271	0.209
Another tweet	0.637	0.408
Source Characteristics		
Followers	3.563***	0.757*
Followings	0.545	1.400
Tweets	0.313	2.892
Favourites	2.718***	0.648***
Membership age	1.073	2.976
Verification status	2.519**	0.757***

**** p<.01, ** p<.05, * p<.1*

5. Discussion

Social networking sites are widespread platforms that directly disseminate health knowledge and information to society (Abd-Alrazaq et al., 2020). These platforms are potent weapons and can be devastating to public health efforts if they are not used properly. Individuals' information needs and social media sharing behaviours may differ in health emergencies (Pulido

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et al., 2020). During the COVID-19 pandemic, there are notable differences in the dissemination of false and true content. False tweets were retweeted and favoured significantly less frequently than true tweets. In addition, the average number of retweets and favourites for true tweets was considerably higher than for false tweets, indicating that true information is more likely to spread and gain popularity on Twitter. Although this result seems unexpected, previous research observed that during emergencies, people questioned false information more than true information (Castillo et al., 2013). So, individuals tend to favour true information over false ones. One of the reasons might be a high tendency for users with a higher level of experience, followers, and followings to disseminate true information (Bovet & Makse, 2019). Another reason might also be explained by cognitive dissonance theory (Harmon-Jones & Harmon-Jones, 2008). Users are likelier to engage with information that aligns with their beliefs and interests. Accepting contradictory information would create dissonance, which people are motivated to avoid. Individuals might also engage in confirmation bias, seeking information that confirms their pre-existing beliefs and disregarding information that contradicts their beliefs (Nickerson, 1998). True tweets may be more likely to meet these criteria than false tweets. Lastly, the higher percentage of verified accounts in the true tweets dataset could imply that verified users are more cautious and responsible while sharing information during that period. Individuals are more likely to accept and share information from sources they perceive as credible and trustworthy (Birnbaum & Mellers, 1983). So, a higher level of trust is associated with verified accounts, which yield more retweets and favourites.

Nevertheless, the user experience could turn the tide. False tweets posted by more experienced accounts may benefit from a more extensive network of followers and a more established online presence, which could lead to more retweets. According to the innovation diffusion theory, the novelty of a message plays a crucial role in its spread on social media (Rogers, 2010). A novel message is more likely to attract attention and be shared by users. However, in the case of true tweets posted by experienced users, the content may not be perceived as novel, as similar information may have already been shared before. As a result,

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users may not find the content attention-grabbing and may be less likely to share it, leading to fewer retweets. This effect is amplified by the fact that experienced users tend to have a large follower base and may share already widely known information, reducing the novelty of their tweets even further.

False tweets and true tweets also have notable differences in their writing style. False tweets tend to use more punctuation marks such as question marks, exclamation marks, and ellipses in addition to more capital letters, which may indicate an attempt to catch the reader's attention and create a sense of urgency, excitement, or emphasis. Despite the misinformation, it might result in greater visibility and engagement among users. On the other hand, true tweets contained more only capital letters, media, hyperlinks, emoticons, mentions, and hashtags, which may indicate a more thoughtful and informative approach to communication. Including media and hyperlinks in tweets may suggest a desire to provide evidence or support the presented information. At the same time, emoticons and hashtags may indicate an attempt to create a sense of community or engagement with readers. Media use might increase the number of likes, but tweets with hyperlinks and hashtags are less retweeted and favoured. Posts with hyperlinks require users to click the link to access additional information. This can be time-consuming and may not be preferred by users who want to scroll through their feeds quickly. Additionally, users may be wary of clicking on hyperlinks from sources they are unfamiliar with or do not trust. This could further contribute to lowering retweet rates for posts with links. Moreover, some users may find hashtags distracting or annoying; therefore, they may be less likely to engage with tweets that include them. Such tweets may appear less authentic or more promotional, which could turn off some users. They may also be seen as spammy, which could lead to users disliking or ignoring them. Finally, it is also possible that tweets with hashtags do not resonate with users, so they receive fewer likes.

Additionally, the results reveal that social media users responded negatively to emotional elements. Each additional negative sentiment score reduced the retweets, highlighting the importance of presenting information positively and engagingly to increase its likelihood of being shared. It could suggest they are skeptical about the content's truthfulness, emphasizing emotions, and showing a particular media literacy level (Burkhardt, 2017).

By paying attention to these writing style differences, social media users can become more informed and better equipped to navigate the vast amount of information on social media (Apuke & Omar, 2020b). For practitioners such as fact-checking organizations, governments, and businesses, the differences in writing style can help develop strategies to combat misinformation. Firstly, fact-checking organizations can use these differences to identify and flag potential false content. For example, false tweets with excessive punctuation marks and capital letters may be flagged as potentially misleading or false, prompting further investigation. However, fact-checking resources require extensive manual labour (Zhang & Ghorbani, 2020). So, the findings can be used to develop AI algorithms to combat misinformation more effectively. AI algorithms can be trained to identify the characteristics of tweets indicative of false information. Governments and public health organizations can also benefit from these suggestions by using them to improve their own communication strategies. They can adopt a more informative and thoughtful approach to their content, incorporating media, hyperlinks, and hashtags to provide more evidence and support for their messages. This could help to combat the spread of false information and promote accurate and reliable information related to public health and safety. In such a way, they could increase public health literacy, which is the key to fighting an infodemic (Medford et al., 2020). Businesses can also use these suggestions to improve their social media marketing strategies by creating engaging and informative content that resonates with their audience.

The ramifications of misinformation dissemination cannot be overstated (Balli et al., 2020). Its pervasive spread can substantially impact the flow of critical information concerning politics, economics, and public health, ranging from the government to ordinary citizens. Misinformation can threaten democratic institutions by altering public opinion, creating division and discord, and affecting election outcomes. Economically, it can cause harm to businesses, consumers, and markets by disseminating false information about products, services, and

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financial performance. Moreover, the consequences of misinformation can be life-threatening, especially in the context of health, where it can impact medical advice and exacerbate the spread of diseases.

6. Conclusion

This study examined tweet messages and source characteristics to investigate their role in misinformation dissemination on Twitter during the COVID-19 pandemic. We found that tweets with either extremely positive or negative sentiments were less likely to be retweeted, and those containing hyperlinks were also retweeted less frequently than those without hyperlinks. Verified and more experienced users were more likely to have their tweets retweeted and favoured by others. Additionally, tweets that included media such as photos or videos were likelier to be liked by others. However, tweets with excessive capital letters were less favoured. Interestingly, a tweet written in all capital letters that conveyed true information tended to be more favoured. While the characteristics of messages were not significant in differentiating between true and false content, the source credibility features had a moderating effect on the spread of information. Unfortunately, our study was limited to the English language and the COVID-19 pandemic, and our dataset was incomplete due to deleted or private posts. Therefore, our findings may not be generalizable to other social media platforms, languages, or topics, and we encourage future research to explore these areas to increase the generalizability of our findings.

7. Ethics Statement

We obtained permission from Twitter to access their API for our research (*Twitter Developers*, n.d.). We collected data available to the public and did not require user consent (Eysenbach & Till, 2001; Frankel & Siang, 1999). We took measures to ensure that the user accounts in our dataset remained private and confidential.

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Appendix A

Keywords and hashtags used by Memon and Carley (2020) for data collection.

Type	Terms
Keywords	bleach, vaccine, acetic acid, steroids, essential oil, saltwater, ethanol, children, kids, garlic, alcohol, chlorine, sesame oil, conspiracy, 5G, cure, colloidal silver, dryer, bioweapon, cocaine, hydroxychloroquine, chloroquine, gates, immune, poison, fake, treat, doctor, senna makki, senna tea
Hashtags	#nCoV20199, #CoronaOutbreak, #CoronaVirus, #CoronavirusCoverup, #CoronavirusOutbreak, #COVID19, #Coronavirus, #WuhanCoronavirus, #coronaviris, #Wuhan

Appendix B

Tweet categories and counts presented by Memon and Carley (2020).

Category	**Count**
Irrelevant	131
Conspiracy	924
True treatment*	0
True Prevention*	175
Fake Cure*	141
Fake treatment*	34
False Fact or Prevention*	321
Correction/Calling Out	1331
Sarcasm/Satire	476
True Public Health Response*	163
False Public Health Response*	3
Politics	512
Ambiguous/Difficult to Classify	143
Commercial Activity or Promotion	37
Emergency Response	17
News	95
Panic Buying	70

* Included categories in the study