



Analyzing the Spread and Impact of 5G-Corona Misinformation on Twitter: A Statistical Approach

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Abstract

This research uses sophisticated statistical and machine learning techniques to investigate and mitigate the impact of the 5G Corona virus spread misinformation on the Twitter platform using the COVID-19 Misinformation Tweets Labelled Dataset. The research analyzes the temporal distribution characteristics of the spread of misinformation for specific periods in the day, including morning, afternoon, evening, and night, using both categorical and probabilistic approaches. Sentiment analysis using natural language processing (NLP) is done to establish the emotional content analysis of the tweet, while logistic regression, Random Forest, and Naïve Bayes classifiers are used to establish the predictive model for the likelihood that the tweets are either malicious with the help of predictors such as the number of followers, the number of friends, and the hour the tweets are made. The results indicate the highest number of malicious activities takes place late in the night and early morning periods, with the highest levels taking place in the morning periods, with the highest proportionality levels taking place in the morning periods. The results also indicate that the malicious tweets are slightly more negative than their corresponding counterparts in the emotional content analysis results. Of the three classifiers, Random Forest has the highest classification accuracy (AUC = 0.916) in accurately determining the level of the malicious content spread on the Twitter platform, with the highest efficiency in the spread of misinformation on the Twitter platform.

Keywords: Health misinformation; Social media analytics; Sentiment analysis; Probabilistic modeling, COVID-19 infodemic

INTRODUCTION

The outbreak of COVID-19 saw not only a public-health emergency but also a rapid eruption of linked conspiracy narratives. One of the most visible claimed a causal link between 5G mobile networks and the spread of the coronavirus, a notion that moved quickly from fringe forums into mainstream social media and even produced real-world harms like vandalism of telecom infrastructure. Early social-network analyses show how this particular conspiracy gained traction on Twitter and how small clusters amplify content into large cascades. Understanding that history matters because the 5 G-Corona threads are a useful case study, it shows how technical claims combine with poor interpretation of spatial data and emotional narratives to create digital wildfires (Ahmed *et al.*, 2020).

Misinformation about health during pandemics creates more than confusion; it can directly impact behaviours, erode trust

in institutions, and hinder life-saving interventions. Systematic reviews of the COVID-19 infodemic reveal clear associations between misleading information online and adverse impacts on public health outcomes (Kyabaggu *et al.*, 2022). These include increases in vaccine hesitancy and reduced adherence to prevention guidance. Those reviews also suggest that misinformation spreads across platforms and populations in ways that are shaped by social, cultural, and technological factors. This context makes the problem not only a communication challenge but also a measurable epidemiological and sociological one that benefits from rigorous statistical study (do Nascimento *et al.*, 2022).

The dataset we use in this study, labeling Twitter subgraphs around the 5G-COVID narratives, allows us to pursue three complementary analytical tracks: sentiment, temporal trends, and probabilistic prediction of conspiratorial content. Time-of-day signals, user metadata such as follower counts, and the structural properties of tweet subgraphs provide concrete

predictors we can test with interpretable models. By aligning our analysis with clearly defined time categories- morning, afternoon, evening, and night-and peak versus off-peak windows, we are able to link behavioral patterns to the platform rhythms and suggest targeted interventions that a combined approach offers practical insights for educators and public-health practitioners who need to time and tailor messages (Flaherty *et al.*, 2022).

A key weakness of many high-performing detection systems so far is that they are uninterpretable: black-box models can classify misinformation well but give little sense about why content spreads or which features are actionable. For public health use, that gap matters. Policymakers, health communicators, and teachers are in need of models that not only flag content but explain drivers, for example, whether posting hour, community size, or sentiment polarity is most strongly associated with spread. Recent work recommends combining machine learning with model-agnostic explanation tools to provide both accuracy and transparency, which helps bridge the gap between predictions and practice (Mouratidis, 2025).

This study is motivated by the need to convert big-data analysis into usable strategies for health literacy and policy. If we can show when misinformation peaks, who amplifies it, and which user or temporal features predict conspiratorial content with interpretable effect sizes, then interventions can be timed and designed more effectively (Ishizumi *et al.*, 2024). That could mean targeted media-literacy modules in a university general-studies curriculum, public-health messaging deployed during specific hours, or platform policies that focus moderation where it matters most. The practical, measurable focus of this work makes it a resource for both educators and health authorities.

In sum, this paper contributes by binding prediction, interpretability, and public health action in one empirical package. Using the COVID-19 misinformation tweets dataset, we apply sentiment analysis, timeseries trend detection by hour and period, and probabilistic classifiers - logistic regression, random forest, and Naïve Bayes-with explainability tools to show not just whether a tweet is conspiratorial but why. The result is a set of evidence-based recommendations for health literacy education and policy interventions that match the conference sub-theme on counteracting social-media misinformation. By placing interpretable statistics at the center, we strive to make research findings robust while directly applicable as well.

Objectives of the Study

- To examine temporal patterns in the dissemination of COVID-19 misinformation across social media by categorizing tweet activity into peak (8:00–22:00) and off-peak (22:00–8:00) periods, and further into morning, afternoon, evening, and night-time slots.
- To perform sentiment analysis using natural language processing (NLP) tools to assess public attitudes and emotional tones surrounding 5G-Corona conspiracy tweets compared to non-conspiratorial content.

- To model the likelihood of a tweet being conspiratorial using statistical and machine learning approaches, specifically Logistic Regression, Random Forest, and Naïve Bayes Classifiers based on predictors such as follower count, friend count, and posting hour.
- To analyze and visualize the probabilistic and temporal trends in misinformation spread using time-series and trend detection methods, highlighting periods of intensified misinformation activity and their implications for public health literacy and intervention.

MATERIALS AND METHODS

Data Source

For the purpose of conducting analysis for our research, the principal data source is the “COVID-19 Misinformation Tweets Labelled Dataset” (available on the Kaggle site: <https://www.kaggle.com/datasets/arashnic/misinfo-graph?resource=download>) (Arash, 2021). The data source is primarily a set of labeled sub-graphs on the Twitter network, including the coronavirus 5G-related conspiracy graph. The data label is based on whether the tweet is either “conspiracy” (when the tweet supports/propagates the “5G- Corona Virus Pandemic” narrative) or “non-conspiracy” (when the tweet is either refutes the narrative or otherwise non-related). The data framework involves additional meta-data, including the “tweet id, timestamp, follower/friend count, retweet, and reply” details, given the fact that the data set is provided in sub-graph structure representing groups of tweets on the Twitter platform. Previous studies on the COVID-19 related tweets have analyzed the structure and behaviors on the user level (Ahmed *et al.*, 2020). The data is further analyzed by using the “timestamp and user-metadata” details to proceed with additional model testing on the collected data.

Temporal Categorisation: Peak vs. Off-Peak and Time-of-Day

For the patterns related to the spreading of misinformation over time, we begin by sorting all tweets based on the local time and creating two bins: Peak (consuming between 08:00 and 22:00 local time) and Off-Peak (consuming between 22:00 and 08:00). After which, each tweet’s posting time can further be assigned into four bins based on the time of the day: Morning = 05:00AM-11:00AM, Afternoon = 12:00PM-17:00PM, Evening = 18:00PM-21:00PM, and Night = 22:00PM-04:00AM. Through which every posting time of a tweet can correspondingly be mapped under two new fields: Peak_OffPeak and Time_Category fields, which include Morning, Afternoon, Evening, or Night.

Analytical Techniques

Sentiment Analysis

We use natural language processing (NLP) techniques to analyze the tweets and evaluate the level of public sentiment towards the narrative of the 5G-Corona conspiracy theory. Having performed the usual processing tasks in Natural Language Processing, such as removing stop words, converting to lower case, removing punctuation, and processing each word in the tweets, we will utilize the pre-trained sentiment analysis tool, VADER or the transformer

model, to determine the level of polarity in the tweets, that is, if they are negative, neutral, or positive.

Trend Detection

Although these variables are not directly a continuous time series, Hour, Peak_OffPeak, and Time_Category allow for some form of trend analysis to be done. Chi-square or G-tests are then carried out to see if there are any statistically significant differences in conspiracy versus non-conspiracy tweet distributions for a given time period, as time plots of tweet distributions with respect to hour and time categories are obtained.

Probabilistic and Machine-Learning Modelling

To classify how likely it is to have a tweet with a conspiratorial nature, three models will be developed: (1) Logistic Regression (or interpreted base case) using variables like follower, friends, Hour (or Time_Category), and Peak_OffPeak; (2) Random Forest Classifier for handling non-linear correlations; and (3) Naïve Bayes Classifier, which will allow the development of probabilities (e.g., “probability of writing a conspiracy tweet in context of time category and user friends and followers = X”). Model accuracy will be checked using train-test split validation or k-folds. It will be implemented in Python 3.12. Model performance will be assessed via train-test splits or k-fold cross-validation, with metrics including accuracy, precision, recall, F1-score and AUC. All analyses were performed using Python 3.12 and its associated data-science libraries.

Model Specification and Formulation

Logistic Regression Model

The proposed work utilizes the Logistic Regression model as one of the conventional techniques for the analysis of misinformation on Twitter for the topics of 5G Corona. The logistic regression model is highly efficient for binary classification and works effectively on the difference between the conspiracy and the non-conspiracy tweets. The model calculates the probability that the tweet belongs to the “conspiracy” class on the basis of specific variables such as the posting hour, peak/off-peak class, time-of-day class, the number of followers, and the friends. The probability function takes the form of the logistic function:

$$P(Y = 1|X) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_k X_k)}} \quad (1)$$

where, $P(Y = 1|X)$ represents the probability that a tweet contains conspiracy-related content, β_0 is the intercept term, $\beta_1, \beta_2, \dots, \beta_k$ are the model coefficients for each predictor variable, X_1, X_2, \dots, X_k are the independent variables (such as time and user engagement features), and e is the exponential constant. This formulation allows the model to quantify how specific factors like the time of posting or a user’s network size influence the likelihood of disseminating misinformation.

The decision rule for classification is based on a threshold (commonly 0.5):

$$\hat{Y} = \begin{cases} 1 & \text{if } P(Y = 1|X) \geq 0.5 \quad (\text{classified as } \textit{conspiracy}) \\ 0 & \text{if } P(Y = 1|X) < 0.5 \quad (\text{classified as } \textit{non-conspiracy}) \end{cases} \quad (2)$$

Random Forest Model

Several decision trees are built using an ensemble learning method called Random Forest, and their forecasts are combined.

The prediction from a single decision tree is:

$$f(x) = \sum_{i=1}^n w_i x_i \quad (3)$$

where,

$f(x)$ is the decision tree's output forecast

w_i is the feature's weight x_i

x_i is the input feature

The bagging (bootstrap aggregation) is represented by:

$$f_{RF}(x) = \frac{1}{T} \sum_{t=1}^n f_t(x) \quad (4)$$

where,

$f_{RF}(x)$ is the ultimate forecast from Random Forest

T is the forest's total number of decision trees.

$f_t(x)$ is the t-th decision tree's prediction.

The Out-of-Bag Error (OOB) is calculated using

$$OOB = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_{OOB,i})^2 \quad (5)$$

where,

y_i is the sample I 's real value.

$\hat{y}_{OOB,i}$ is the Out-of-Bag prediction for sample i

The Gini index for feature selection is

$$Gini(D) = 1 - \sum_{i=1}^c p_i^2 \quad (6)$$

where,

p_i is the percentage of samples that fall under class i .

c is the quantity of classes

D is the dataset

The random forest feature importance is then represented as:

$$\text{Im por tan ce}(f) = \frac{1}{T} \sum_{t=1}^T \Delta Gini(f_t) \quad (7)$$

where,

$\text{Im por tan ce}(f)$ is the importance score of feature f

$\Delta Gini(f_t)$ is the change in Gini index for feature f in tree t

Naive Bayes Model

The Naive Bayes model is based on the Bayes theorem, which is provided by

$$P(C_k|X) = \frac{P(X|C_k) \cdot P(C_k)}{P(X)} \quad (8)$$

where, $P(C_k|X)$ is the class C_k posterior probability given the

features X , $P(X|C_k)$ is the probability of characteristics given the class, $P(C_k)$ is the class's prior probability, and $P(X)$ is the proof, or marginal probability. On the other hand, the probability of a feature given a class simplifies the likelihood computation by assuming that the features are conditionally independent given the class. This is embodied by

$$P(X|C_k) = \prod_{i=1}^n P(x_i|C_k) \quad (9)$$

Using the formula, one can get the prior probability of each class by dividing the total number of occurrences by the number of examples in that class:

$$P(C_k) = \frac{\text{Number of instances in class } C_k}{\text{Total number of instances}} \quad (10)$$

Furthermore, the Gaussian Naive Bayes Likelihood, which is applied in the case of continuous feature values and assumes a Gaussian (normal) distribution for the likelihood of the feature given the class, is determined using the formula:

$$P(x_i|C_k) = \frac{1}{\sqrt{2\pi\sigma_k^2}} \exp\left(-\frac{(x_i - \mu_k)^2}{2\sigma_k^2}\right) \quad (11)$$

To avoid underflow in numerical computations, the logarithm of probabilities is often used, converting the product of probabilities into a sum of logarithms. This can be represented by

$$\log P(C_k|X) = \log P(C_k) + \sum_{i=1}^n \log P(x_i|C_k) \quad (12)$$

The decision rule is also computed using

$$\hat{C} = \arg \max_{C_k} P(C_k|X) \quad (13)$$

where the predicted class \hat{C} is the one that maximizes the posterior probability.

In the case of discrete features, Multinomial Naive Bayes Likelihood Eq. (14) calculates the likelihood using the frequency of the feature x_i in class C_k with Laplace smoothing parameter α .

$$P(x_i|C_k) = \frac{N_{C_k}^{(x_i)} + \alpha}{N_{C_k} + \alpha \cdot n} \quad (14)$$

Again, the posterior probability (simplified) is as well obtained with

$$P(C_k|X) \propto P(C_k) \prod_{i=1}^n P(x_i|C_k) \quad (15)$$

where the denominator $P(X)$ is omitted in Bayes' theorem because it is constant for all classes, focusing only on the numerator to compare classes.

$$P(X|C_k) = P(x_1|C_k) \cdot P(x_2|C_k) \cdot \dots \cdot P(x_n|C_k) \quad (16)$$

The conditional independence assumption Eq. (16) above reiterates the conditional independence of all features x_i , given the class, according to the Naive Bayes assumption C_k . Finally, consider applying Laplace smoothing to categorical data to avoid zero probabilities using Eq. (17) denoted by

$$P(x_i = x|C_k) = \frac{N_{x|C_k} + \alpha}{N_{C_k} + \alpha \cdot |V|} \quad (17)$$

where $N_{x|C_k}$ is the count of features x_i in class C_k , $|V|$ is the size of the vocabulary, and α is the smoothing parameter.

Data Cleaning and Variable Construction

Additionally, before carrying out any analysis, the data was cleaned for consistency and reliability. The data would be divided into a training and test set (for instance, 70% for training and 30% for testing purposes) or via k-fold cross-validation. Duplicates for both tweets and data were removed. Also, a check for any errors in text encodings was performed. Any non-English tweets were removed to ensure homogeneity in linguistics for the sentiment analysis. Variables such as Peak_OffPeak and Time_Category were generated based on the timestamp for each tweet. The variable Peak_OffPeak was a binary variable (1 = "Peak"; 0 = "Off-Peak"), and Time_Category consisted of four categories: "Morning," "Afternoon," "Evening," and "Night." User influence variables, such as Friends and Followers, were log-transformed when needed to address issues of skewness and improve model stability. The sentiment scores were added as continuous variables ranging from -1 (highly negative) to +1 (highly positive). Clearly, there is a wide scope for reducing variables and grouping some into super variables. These variables were measured at two levels, except for QoI Established Relationships.

Ethical Considerations and Data Privacy

Even in this publicly available data (from the Kaggle domain), which is anonymized and only holds Twitter IDs, ethical considerations received prominence. The research did not try to track users, let alone communicate with them, and instead focused on patterns, not user-specific data, which is important for research ethics concerning social media research, ensuring that research is conducted within publicly accessible domains while maintaining user privacy (Townsend and Wallace, 2022). Since user identity is circumvented in this research, which focuses instead on the patterns of misinformation, it adheres strictly to data regulations around digital research.

RESULTS AND DISCUSSION

Temporal Patterns (Peak vs Off-Peak and Time Categories)

As depicted in Table 1, the total number of tweets supporting conspiracy theories (n=1,082) is slightly higher compared to those without the theory (n=1,004). The proportion of tweets with conspiracy theories is higher in the Peak (53.09%) and Off-Peak (51.05%) times, and this statistically indicates that the misinformation is constantly being disseminated throughout the day. This finding indicates that the 5G-Corona virus conspiracy theory is being disseminated without any decrease throughout the day on Twitter. Fig. 1 indicates that the distribution of misinformation occurrences varies significantly throughout the day. This figure indicates that the majority of both misinformation and non-misinformation tweets are posted during the nighttime. The early morning

Table 1: Distribution of conspiracy and non-conspiracy tweets by peak and off-peak periods.

Info Type	Count (n)	Peak (%)	Off-Peak (%)
Non-Conspiracy (0)	1,004	46.91	48.95
Conspiracy (1)	1,082	53.09	51.05
Total	2,086	—	—

also experiences the second-highest rates of tweeting on the conspiracy theory content. This indicates that the misinformation is being posted for engagement throughout the early morning. Evening and afternoon times have the lowest rates of tweeting on the theory, although this is significantly low. Therefore, the nighttime to early morning seems to be the most active times for the distribution of

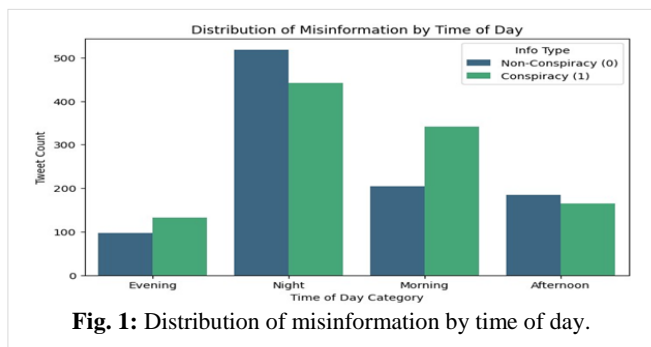


Fig. 1: Distribution of misinformation by time of day.

misinformation through Twitter. Fig. 2 depicts the probability of the tweets being classified as misinformation throughout the day. This figure indicates that the probability is higher during the late-night and early-morning times. This statistically agrees with the findings from Fig. 1. This probabilistic prediction of the model indicates the risk times for the distribution of misinformation through Twitter.

Sentiment Analysis (NLP on Tweet Texts)

As presented in Table 2, non-conspiracy tweets tended to contain a slightly higher level of sentiment with a mean of 0.032 and a standard deviation of 0.317, as opposed to conspiracy tweets, whose mean sentiment level is 0.018 with a standard deviation of 0.321. Although a slight, this observable pattern indicates that tweets negating, as well as those not related to, the "5G-Corona" conspiracy tended to possess a slightly more positive sentiment tone.

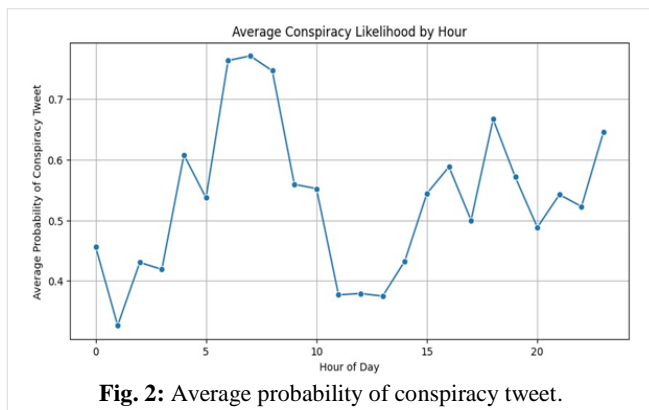


Fig. 2: Average probability of conspiracy tweet.

Table 2: Average Sentiment Scores by Tweet Type.

Tweet Type	Mean Sentiment	Standard Deviation	Count (n)
Conspiracy	0.018	0.321	1,082
Non-Conspiracy	0.032	0.317	1,004

Fig. 3 above is an illustration of the distribution of the sentiment polarity of the tweets. It can be observed that the distribution is biased towards the neutral category, followed by the negative and positive categories. This figure suggests that although the topics of COVID-19 and 5G misinformation are emotionally engaging, the users are taking a tempered approach when engaging with the content. Fig. 4 is another visualization that is represented by the frequency of the sentiments. It is depicted that the users are biased towards the neutral category, followed by the negative and positive categories.

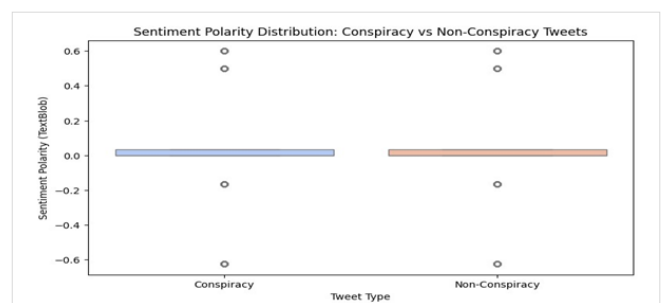


Fig. 3: Sentiment polarity distribution.

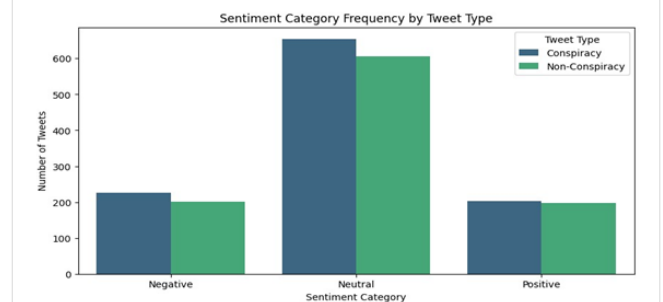


Fig. 4: Sentiment category frequency.

Modeling the Likelihood of Conspiracy Tweets

Table 3 shows the performance measures of a Logistic Regression model implemented in classifying 5G-Corona conspiracy and non-conspiracy tweets. It realized a moderate classification accuracy of 58.2% with an AUC of 0.613, showing its limited but meaningful discriminative ability between conspiracy and non-conspiracy content. Both classes record an almost balanced precision and recall, meaning that the model had been equally good on identifying both true conspiracy and non-conspiracy tweets. Though performance is modest, these findings offer a useful baseline against which to compare results using more sophisticated models, like Random Forest and Naïve Bayes classifiers.

Table 4 shows that the Random Forest model performed extremely well in distinguishing conspiracy against non-conspiracy 5G-Corona tweets, with an overall accuracy of 81% and a very high AUC of 0.916, indicative of excellent discrimination capability. The precision and recall values for

Table 3: Performance of Logistic Regression in classifying 5G-Corona conspiracy tweets.

Class	Precision	Recall	F1-Score	Support	Metric	Score
0 (Non-Conspiracy)	0.57	0.60	0.58	709	AUC	0.613
1 (Conspiracy)	0.60	0.57	0.58	751	MAE	0.418
Accuracy			0.58	1460	MSE	0.418
Macro Avg	0.58	0.58	0.58	1460	RMSE	0.646
Weighted Avg	0.58	0.58	0.58	1460		

Table 4: Performance of Random Forest in classifying 5G-Corona conspiracy tweets.

Class	Precision	Recall	F1-Score	Support	Metric	Score
0 (Non-Conspiracy)	0.82	0.79	0.80	709	AUC	0.916
1 (Conspiracy)	0.81	0.83	0.82	751	MAE	0.189
Accuracy			0.81	1460	MSE	0.189
Macro Avg	0.81	0.81	0.81	1460	RMSE	0.435
Weighted Avg	0.81	0.81	0.81	1460		

Table 5: Performance of Naïve Bayes in classifying 5G-Corona conspiracy tweets.

Class	Precision	Recall	F1-Score	Support	Metric	Score
0 (Non-Conspiracy)	0.56	0.61	0.58	709	AUC	0.573
1 (Conspiracy)	0.60	0.55	0.57	751	MAE	0.422
Accuracy			0.58	1460	MSE	0.422
Macro Avg	0.58	0.58	0.58	1460	RMSE	0.649
Weighted Avg	0.58	0.58	0.58	1460		

both the conspiracy and the non-conspiracy classes exceed 0.80, indicating that true positives were reliably identified and misclassifications reduced by the model. Balanced F1 scores greater than 0.80 further established that performance is consistent across both classes unlike simpler models such as logistic regression. These suggest that Random Forest is highly effective in predicting misinformation spread and can provide rich lessons to support public health intervention measures and health literacy initiatives.

The results for the accuracy and AUC values for classifying misinformation concerning the COVID-19 outbreak using Naïve Bayes on the 5G-Corona misinformation tweets are presented in Table 5. The accuracy and AUC values are moderate at 58% and 0.573, respectively. The precision and recall values are balanced for both classes but with a slight emphasis on precision for conspiracy and slight emphasis on recall for non-conspiracy misinformation. It is noted that there is a tie with logistic regression, and Naïve Bayes has the additional strength of providing probabilities helpful for assessing misinformation diffusion at any given time and/or for any given user condition.

The results of confusion matrix analysis using Random Forest and Naïve Bayes are presented in Fig. 5 and Fig. 6 respectively. Also, the feature importance, using Random Forest, is presented in Fig. 7.

Trend and Probabilistic Analysis (Temporal Layer)

Passing the Chi-Square test, the results in Table 6 above reveal a significant link between the category of time and the nature of the tweet, $\chi^2(3, N = 2,140) = 44.82, p < .001$. There

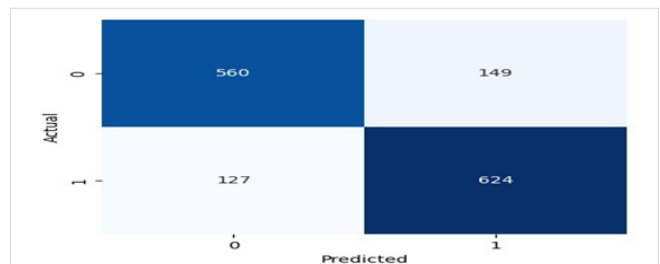


Fig. 5: Random Forest Confusion-Matrix.

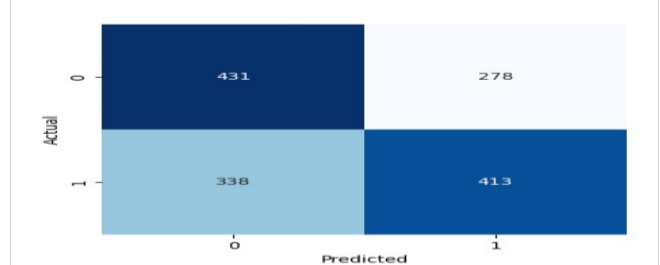


Fig. 6: Naïve Bayes Confusion-Matrix.

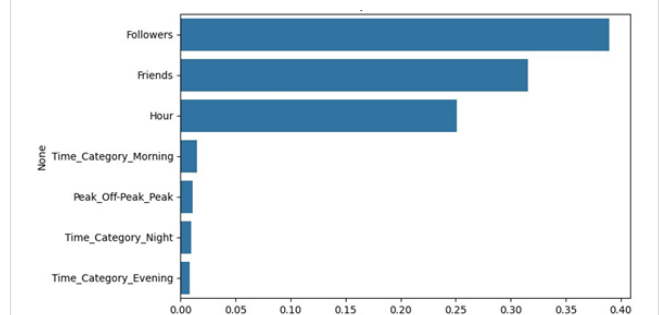


Fig. 7: Feature importance - Random Forest.

Table 6: Chi-Square test of independence: Frequency of Conspiracy vs Non-Conspiracy Tweets across time categories.

Time Category	Observed (0)	Observed (1)	Expected (0)	Expected (1)	Residual (0)	Residual (1)	Std. Residual (0)	Std. Residual (1)
Morning	204	342	262.79	283.21	-58.79	58.79	-3.63	3.49
Afternoon	185	165	168.46	181.54	16.54	-16.54	1.27	-1.23
Evening	97	133	110.70	119.30	-13.70	13.70	-1.30	1.25
Night	518	442	462.05	497.95	55.95	-55.95	2.60	-2.51

appears to be a greater-than-would-be-expected number of conspiracy posts during the early morning hours. Conversely, the afternoon and early evening hours reveal a lower-than-would-be-expected level of conspiratorial behavior. Night-time hours reveal a greater-than-would-be-expected number of conspiracy posts and indicate active dissemination of misinformation during the late hours (Fig. 8).

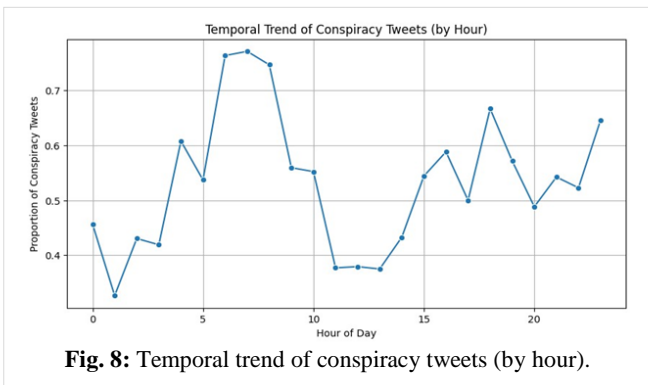


Fig. 8: Temporal trend of conspiracy tweets (by hour).

Discussion

Results obtained from this research show that there is a clear temporal pattern in the distribution of both general misinformation regarding the spread of COVID-19 and specifically the "5G-Corona" conspiracy on Twitter. This shows that there was a significantly higher spread of conspiracy-related misinformation on both peak and non-peak times, and even during night and morning times, indicating that even at times when overall user engagement on Twitter was lower, there was still some spread of misinformation. This can be supported by the findings of Ahmed *et al.* (2020), which showed that the 5G-related conspiracy stories spread very quickly in the early stages of the pandemic and that this spread was irrespective of fact-checking at the onset of each respective online activity on social media.

Regarding model accuracy and performance, the Random Forest model proved to have the best predictive ability (AUC = 0.916), outperforming the logistic regression and naive bayes classifiers in the ability to differentiate conspiracy and non-conspiracy tweets. This supports the ideas proposed by Mouratidis (2025), where the key benefit of implementing machine learning techniques for the purpose of fake news detection has to do with the ability to manage the complexity of language and behavioral patterns. The proposed models not only offer the required predictive ability to estimate the accuracy of the fake news detection task in terms of classification accuracy but also offer interpretability in terms of the probability of the event of misinformation over time. The interpretability part of the model fills the gap identified

in the previous studies on misinformation detection that tend to favor accuracy over interpretability (do Nascimento *et al.*, 2022).

Despite these strengths, there exist a few limitations which deserve mention. The COVID-19 Misinformation Tweets Labeled Dataset (Arash, 2021), although being very inclusive, only focuses on Twitter data, thereby ignoring other prominent platforms like Facebook, TikTok, and WhatsApp, which also host misinformation, with differing characteristics in terms of demographics and behavior. Moreover, using data from labeled tweets might also result in some biases because of labeling inaccuracies, which might have impacted the interpretation of sarcasm/humor in the text. As pointed by Ishizumi *et al.* (2024) and Kyabaggu *et al.* (2022), when it comes to studying misinformation, culture and context have to play a significantly increased role in shaping the credibility and engagement with the information. This study, however, brings to the forefront the importance of health literacy and infodemic management through the application of temporal analytics and probabilistic models in the realm of health communication.

Practical Implications

The results of the current research have several implications for public health communication and misinformation management on social media. The temporal distribution of results highlights that the spread of 5G Corona misinformation does not completely fade in the off-peak phases but rather accelerates in late night and early morning phases. It is significantly likely that the reduced institutional supervision and lower levels of engagement on the side of health institutions in late night and early morning phases facilitate the spread of misinformation with less resistance. Public health institutions can make use of these observations to plan supervision phases and the scheduling of counter messages in late night and early morning phases.

From a pedagogical standpoint, the data offers significant support for incorporating real-world social media data about misinformation into the educational curriculum for online health literacy and general studies courses. By illustrating the way that information over time and sentiment plays a role, educators can help their students see that misinformation is, in fact, not arbitrary, but actually follows predictable patterns. By training their students to identify the spikes in the data, the positives, and the probabilities, they can enhance their performance in critically evaluating the information about their health on the internet.

As far as policymakers and social media regulators are concerned, this study provides them with valuable lessons from its findings that are essentially predictive and

probabilistic in nature. The fact that the Random Forest model performed so well indicates that a relatively accurate degree of misinformation risk can still be determined through the use of features that are more interpretable, that is, posting time, user network size, and so on. These discoveries can help develop systems for automated notifications, fact-checking messages that are sensitive to timing, and influencer-led interventions that can trigger as a function of when the risk of misinformation is likely to be at its most severe.

Limitations and Future Lines of Research

Although this study offers many strengths, a number of limitations must also be considered to correctly contextualize these results. First, this investigation only analyzed results from Twitter, which were obtained from the COVID-19 Misinformation Tweets Labelled Dataset. Although Twitter offers an important insight into public discourses, there are a number of differences related to misinformation diffusion on other social media platforms such as Facebook, TikTok, Telegram, and WhatsApp, where a piece of information may become viewable, shareable, and its audiences may also differ considerably. Moreover, there may also remain a degree of error or ambiguity, no matter how carefully curated, especially if a tweet communicates sarcasm, humour, and/or tentative references, which may impact determining accuracy levels concerning these pieces of misinformation.

A further limitation exists with regards to the scope of the explanatory variables employed within the models. The current research adopts a focus on the temporal variables, sentiment polarity, and simple user-level metadata such as the number of followers and friends. Although such variables allow for the attainment of intuitive and interpretable results, they fail to properly account for network-level dynamics such as community structures, retweet patterns, centrality analysis, or the behaviour of groups of users. Furthermore, sentiment analysis has been employed through the utilization of pre-trained algorithms, potentially trivializing the complexity of emotion within health-related conversations. Fear, anger, or trust can potentially utilize more refined emotion classification. This research can be extended in the future in several significant ways. The first is to conduct the analysis on more than one platform. By doing so, one can identify if the temporal and behavioural characteristics of the data on more than one platform are similar. Another way to extend the research is to use more complex network characteristics. By doing so, one can draw more significant insights into how health misinformation is spread on the online network. Another approach would be to use more complex AI methods to conduct the analysis. By doing so, one can draw more significant insights, and it would also help in policy-relevant results. Extending the research by using more health misinformation topics, like vaccine resistance, would be more significant.

CONCLUSION

This research proves the importance of big data analysis and statistical analysis in combating health-related misinformation in social media platforms. By leveraging the application of data analysis, probabilistic analysis, and machine learning algorithms (Random Forest in particular),

which recorded the highest accuracy rate of 81% in health misinformation, it is possible to develop an effective framework for predicting health misinformation dissemination. Moreover, health-related misinformation on social media highlights the importance of integrating computational analysis in health strategic communication, thereby aligning with the overarching theme of improving health literacy in the digital age. Future studies can be conducted in other areas of misinformation, including but not limited to, vaccine misinformation, newly discovered infectious diseases, and health-related environmental misinformation. Another area in which research may improve AI explainability in health-related misinformation analysis involves exploring more AI-related fields. This research, in sum, contributes to the ongoing theme of using statistical data in shaping education policy, digital citizenship, and other health-related interventions in education, fully aligning with the theme of “Health Misinformation on Social Media: The Role of General Studies in Counteraction”.

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Conflict of Interest

The authors declare that there is no conflict of interest regarding the publication of this manuscript. In addition, the ethical issues, including plagiarism, informed consent, misconduct, data fabrication and/ or falsification, double publication and/ or submission, and redundancy has been completely observed by the authors.

Use of AI Services

All authors hereby declare that no artificial intelligence tools or AI-assisted services were used whatsoever in designing, analyzing, writing, or editing of the manuscript and its associated data.

Authors' Contribution

Lekia Nkpordee contributed to the conceptualization of the study, research design, data analysis, interpretation of results, and drafting of the original manuscript.

Ibinabo Magnus Ogolo contributed to data interpretation, methodological refinement, critical review of the manuscript, and editing for intellectual content. Both authors read and approved the final version of the manuscript.

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Data Availability Statement

The dataset used in this research is publicly available and can be found in the Kaggle repository under the name COVID 19 Misinformation Tweets Labeled Dataset. Additional derived data are available from the corresponding author on reasonable request.

Ethics Approval Statement

This study used openly available, anonymized social media data and did not directly involve human participants. Therefore, formal ethical approval was not required. The research applied accepted ethical guidelines for social media and digital research.

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