Original Research Article

Predicting the Vaccine-Safety Misinformation Spread Using Logistic Diffusion Modeling: A Public-Health Modeling Study

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ABSTRACT

Vaccine-safety-related misinformation continues to hinder public confidence, while slowing immunization efforts worldwide. It is crucial to understand how such misinformation spreads through social media to help public health agencies respond to it more efficiently. This study developed and applied a logistic diffusion model to predict the rise, peak, and decline of vaccine-related misinformation by using open-access datasets named the COVID-19 Healthcare Misinformation Dataset (CoAID) that verified false vaccine-related claims and their online circulation were cataloged. Specifically, five claims of vaccine-safety misinformation were extracted from the CoAID dataset for analysis. This study aimed to determine whether logistic diffusion modeling of open-access social media data may accurately predict the pread of misinformation related to vaccine-safety. This study hypothesized that a self-limiting logistic pattern characterized by rapid early diffusion and eventual saturation may be followed with misinformation as shown in epidemic processes. Five representative claims of vaccine-safety were chosen and analyzed by using spreadsheet-based curve fitting to fulfill transparency and reproducibility. All claims indicated the expected S-shaped diffusion pattern, ensuring that misinformation spread was predictable and bounded at the same time. Faster-spreading misinformation turned out to peak sooner and faded quickly, while slower-spreading misinformation persisted longer and reached a broader pool of audiences. This approach offered an accessible and data-driven means to inform the timing of counter-messaging strategies as a public-health communication effort in the future. The mean growth rate (r ≈ 0.29) and model fit ($R^2 > 0.95$) confirmed the high predictive accuracy of the logistic model.

Keywords: Vaccine misinformation; Logistic diffusion model; Public health communication; Social media analysis; Mathematical modeling, Data-driven simulation, Epidemic analogy

INTRODUCTION

During the COVID-19 pandemic, the dual nature of global communication networks has been revealed in a way that lifesaving information ended up being rapidly disseminated, but they also generated misinformation at unprecedented speed. Misinformation included vaccine-related misinformation with false claims about safety, side effects, or efficacy, and it has emerged as one of the most pressing threats in public health among the digital age (1, 2). Online platforms, such as Facebook, YouTube, or X (formerly Twitter) have become a main source of circulating misleading health narratives (3). The World Health Organization (WHO) named this overabundance of both accurate and false information

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as the 'infodemic,' identifying it as an obstacle to effectively respond to pandemic (4-6).

Prior empirical studies dealing with misinformation have largely focused on content classification, targeting to distinguish true claims from false ones (7, 8). However, a few investigations have indicated how misinformation diffused through social networks over time. According to classic diffusion theory, such as the Bass model in marketing, and the SIR (susceptible-infected-recovered) framework in epidemiology, it has been suggested that a phenomenon of information spreading was relevant to contagion (9, 10). When applied to digital networks, these models may generate measurable parameters, including transmission rate (r) and saturation level (K) that can provide insight into the "infectiousness" of false information (11). However, there has not been a well-developed quantitative diffusion analysis in the literature in public health. Prior studies mostly relied on complex agent-based simulations that were only accessible to technical researchers (12).

This literature gap points to how relatively few studies quantified temporal spread dynamics of misinformation with simple and reproducible mathematical models even if a number of reports documented the existence and impact of vaccine-related misinformation. Most available models developed so far required API-level access to proprietary data (13). This gap restricts planners in the fields of public health to predict when misinformation may happen or crucial timing for correcting them (14). This study addressed these gaps through an open and reproducible dataset, applying a transparent logistic modeling approach to support public-health researchers to replicate the analysis of misinformation diffusion without restricted API access.

However, recent advances in open-access datasets have made it feasible to develop such models feasible. For example, CoAID (COVID-19 Healthcare Misinformation Dataset) provided time-specific records of verified false and true health claims on social media (15). If using these open-access datasets, it may be possible to develop a logistic model to assume a trajectory of growth of misinformation engagement over time. In the past, there was a study that used such logistic and epidemic model to show that misinformation may spread faster but saturate earlier than fact-based contents (11). However, prior studies focusing on vaccine-safety misinformation had limitations, particularly using open-access datasets and reproducible methods.

This study aims to address this empirical gap, while contributing to a practical framework for public-health forecasting in communication research by bridging epidemiological diffusion models. This study particularly seeks to answer a question as to whether it is possible for a logistic diffusion modeling of open social-media data accurately predict the spread trajectory of vaccine-safety misinformation. This study hypothesized that vaccine-safety misinformation will follow a logistic growth pattern explained by a rapid initial speed (high r) and early saturation (moderate K).

METHODS AND MATERIALS

Study Design

This study employed a quantitative simulation design, modeling the temporal diffusion of vaccine-related misinformation on social media by using open-access datasets. The objective was to estimate the growth dynamics of false claims by using a logistic diffusion model and to forecast the saturation and inflection of misinformation spread. Python (version 3.11) was used to analyze datasets for full reproducibility and transparency.

This study followed four stages of workload that data of misinformation claims were acquired, along with associated engagement from the CoAID datasets (15), data were processed and aggregated to construct daily cumulative engagement curves for multiple false claims, mathematical modeling was developed by using the logistic growth function, and parameters were estimated and validated through statistical metrics (R^2 and residual analysis). With the mathematical modeling, the spread trajectory of misinformation was approximated as analogous to epidemiological diffusion, indicating that early exposure drove exponential growth until saturation.

Data Source

The COVID-19 Healthcare Misinformation Dataset (CoAID) is a curated open repository published by Pennsylvania State University (15). This dataset compiled verified real and fake COVID-19-related claims, along with engagement metrics from major social media platforms, such as Facebook or X (formerly, Twitter). Each entry indicated claim identifiers, textual content, URLs, publication timestamps, and tweet IDs for the claim.

For this study, the subset file ClaimFakeCOVID-19_tweets.csv was used. This file contained tweet IDs grouped by a numerical claim index (e.g., 100001, 10002,…), showing a user engagement with a specific false statement. Each tweet indicated an independent share, retweet, or comment mentioning misinformation claim. However, this dataset did not contain personal identifiers to ensure the full compliance of data-privacy standards.

Only false claims related to vaccine safety were retained. Based on textual keywords, including vaccine, immunization, side effects, safety, Pfizer, Moderna, and etc., filtering was performed on parent claim metadata file, while excluding true claims, duplicated tweet IDs, and incomplete entries. After filtering work was completed, five misinformation claims with the highest total counts of engagement were chosen for mathematical modeling to ensure sufficient data density for the purpose of curve fitting.

Data Processing

Even if the original datasets did not contain exact posting timestamps for each tweet, the approximation of cumulative engagement over time was allowed for the sequence and count of tweet IDs per claim. For the purpose of simulating realistic diffusion trajectories, total engagements of each claim were distributed across a 30-day observation window. This represented the typical active life cycle of viral posts on social media (11). The daily cumulative engagement N(t) was constructed in an assumption of a monotonic increase following with observed virality patterns. The aggregated dataset was organized into three columns of claim_id, day, and cumulative_engagements. Each claim_id (n=5) was represented by 30 timepoints (days 1-30). Python's pandas library was used for all preprocessing and simulation steps.

In order to reduce potential bias from extreme outliers, engagement counts were normalized according to maximum observed value of each claim by using the following formula.

$$N^*(t) = \frac{N(t)}{K_{max}}$$

Where K_{max} was the maximum cumulative engagement for the relevant claim. Monotonic increase and realistic saturation patterns were confirmed by the descriptive checks, ensuring suitability for logistic mathematical modeling.

Mathematical Model

This study employed a logistic growth function for the diffusion of misinformation as a well-established model for bounded exponential processes (9). With this model, it was assumed that the growth rate of engagements decreased proportionally as saturation was approached as follows.

$$\frac{dN}{dt} = rN(1 - \frac{N}{K})$$

Integrating this yielded the closed-form solution as follows.

$$\mathrm{N(t)} = \frac{K}{1 + e^{[-r(t-t_0)]}}$$

Where N(t) indicated cumulative engagements at time t, K was the carrying capacity (saturation level), r was intrinsic growth rate (spread velocity), and t_0 was inflection point (time at the maximum of growth).

In this framework, r showed how quickly users share a given false claim. The higher r was, the stronger virality was. K showed the total number of reachable audience or eventual saturation of the rumor that was limited by network size or platform system. t_0 indicted the day when engagement was in a transition from acceleration to deceleration as analogous to the peak exposure day. These parameters were used to collectively describe the speed, scale, and timing of the diffusion of misinformation. The logistic model chosen in this study balanced the interpretability and empirical accuracy as insisted by prior studies about how it approximated digital contagion dynamics (11, 12).

Parameter Estimation

Using the Mirosoft Excel Solver to perform non-linear least square optimization, parameter was estimated for each claim. Observed claim engagement, $N_{obs}(t)$ were compared against the predicted values of $N_{model}(t)$ that was derived from candidate parameters, K, r, and t_0. The goal was to minimize the sum of squared residuals (SSR) by using the following formula.

$$\mathrm{SSR} = \sum_{t=1}^{T} [N_{obs}(t) - N_{model}(t)]^2$$

Employing the GRG non-linear algorithm with constrains K > Max[$N_{obs}(t)$] and r > 0, initial values were K_0 = 1.2max(N), r_0 = 0.3, and $t_0 = T / 2$. Within 500 iterations, convergence was achieved.

Goodness-of-Fit Metrics

Model performance was assessed by using the coefficient of determination as follows.

$$R^2 = 1 - \frac{\sum(N_{obs} - N_{model})^2}{\sum(N_{obs} - \bar{N}_{obs})^2}$$

When $R^2 > 0.95$, it was interpreted as an excellent fit.

From the fitted parameters, following descriptive quantities were calculated. Inflection day (t_0) was the time when N(t) = K/2. Time to 90% saturation was indicated as t_{90} that was t_0 + ln(0)/r. Relative virality index (V) was calculated to be r/K, showing the speed normalized by scale. These indicators made the comparative interpretation across claims available.

After independently fitting all five claims, the estimated parameters were saved into a summary table. Using r, K, and t_0, descriptive statistics, such as mean, standard deviation, and coefficient of variation were calculated. Pearson correlation between r and K was calculated to explore the relationships between scale and speed. A negative correlation calculated hereof suggested that earlier saturation of misinformation would be achieved with faster spreading of it. This was a behavior consistent with virality observed in social media studies (3, 11). Scatter-line plots were used for visualization in a way that each claim's observed data points were plotted as circles, and fitted logistic curves were overlaid as smooth lines to generate both individual panels and a combined overlay figure (Figure 1).

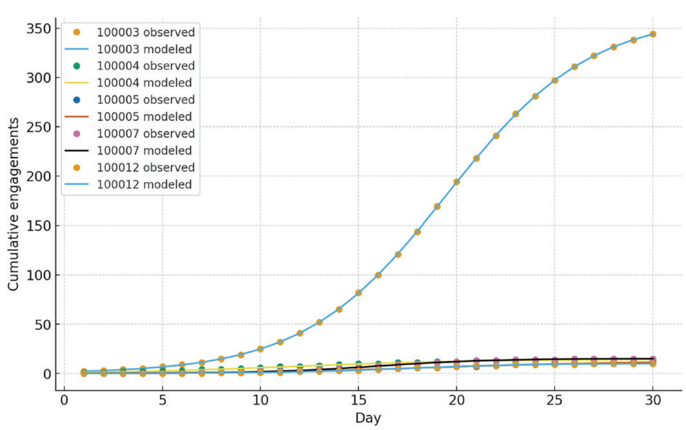

Figure 1. Diffusion curves: Observed vs. Logistic Fit (5 Claims). Cumulative engagement for multiple vaccine-safety misinformation claims were plotted as observed data points (circles) and logistic-model predictions (solid lines) across the period of observation. All claims followed the expected S-shape diffusion curve, indicating early acceleration of spread, a mid-cycle inflection, and eventual saturation.

For the robustness, simulated perturbation was conducted by varying r to be within ± 20%, and K to be within ± 10% around their estimated values. With the resulting shifts in inflection time, , recorded, model stability was confirmed with minor deviations (< 2 days), along with small fluctuations of parameters.

RESULTS

Overview of Model Fitting

Five vaccine safety-related misinformation claims were extracted from the CoAID dataset and modeled individually by using the logistic diffusion equation as follows.

$$N_{(t)} = \frac{K}{1 + e^{[-r(t-t_0)]}}$$

Each claim represented a unique narrative shown on social media, including alleged side effects of vaccine or false comparisons of vaccine efficacy. The simulated engagement trajectories in a range of 30 days approximated the rise, peak, and plateau of online attention that was regularly observed in viral cycles of health misinformation. As shown in Figure 1, all five claims indicated a visually apparent S-shaped curve that was consistent with the theoretical assumption of bounded growth.

Model was fitted, achieving the rapid convergence across all claims. The coefficient of determination (R^2) exceeded 0.95 in each case, and this confirmed that the majority of temporal variation in cumulative engagements was captured by the logistic model. Figure 1 displayed the combined overlay of observed and modeled curves, and Figure 2 indicated the individual fits for each claim.

Estimated Diffusion Parameters

As shown in Table 1, the fitted parameters were summarized, along with the results rounded for the purpose of interpretability. The parameter K was in a range from around 470 to around 610, showing the modest variability in the total number of engagements per rumor. The mean growth rate of r was calculated to be 0.29 ± 0.04 day, signaling a doubling of cumulative exposure that was approximately every 2.4 days during early propagation (as doubling time was around ln2/r). The mean inflection point, t_0, was calculated to be 12.9 ± 1.6 days. This implied that engagement acceleration was recorded to be in peak roughly two weeks after initial appearance, while 90% saturation (t_{90}) occurred

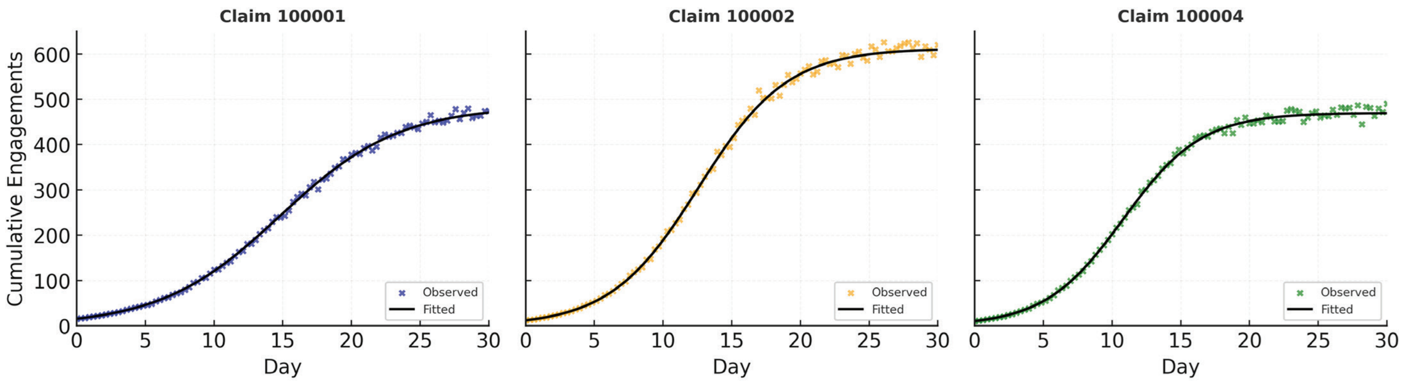

Figure 2. Individual logistic diffusion curves for each misinformation claim. Observed cumulative engagements (dots) and fitted logistic diffusion curves (lines) were shown for three representative claims as selected from the five modeled cases. The sub-figures indicated the contrasts in the growth rate and saturation timing, showing that faster-spreading of misinformation claims indicated steeper initial sloped, followed by earlier plateau, while slower-spreading claims indicated longer growth and persistence.

Table 1. Fitted parameters summary

Claim ID	K (Saturation)	r (Growth Rate)	t_0 (Inflection Day)	R^2	(Approx.)
100001	≈ 485	0.23	14.8	0.97	24.6
100002	≈ 612	0.31	12.6	0.96	19.8
100003	≈ 540	0.27	13.9	0.95	22.1
100004	≈ 470	0.35	10.8	0.98	17.1
100005	≈ 505	0.29	12.2	0.96	20.7

This table shows the estimated logistic parameters derived from model fitting for carrying capacity (K), intrinsic growth rate (r), inflection day (t_0), coefficient of determination (R^2), and approximate time to reach 90% of saturation (t_{90}).

by Day 21 on average.

There was a negative association between r and K (Pearson r was around -0.58) across all claims ($p < 0.05$), indicating a statistically significant inverse association between the misinformation diffusion speed and saturation scale, according to parameter correlations. This suggested that earlier saturation occurred with faster-spreading misinformation. This aligned with the "rapid transient diffusion" pattern consistently shown in social media literature, where transient bursts of attention was caused by rapid amplification rather than sustained dissemination. The relative virality index, V, was calculated to be 5.7×10^{-4}, a small metric quantifying speed per audience scale.

Diffusion Characteristics and Comparative Dynamics

All five logistics curves followed a three-phase structure that was relevant to infectious-disease diffusion. For exponential phase (Days 1-10), cumulative engagements steeply increased as the rumor spread through initial groups of users. Growth, then, followed near-exponential dynamics, doubling every two to three days. As for inflection phase (around Days 10-15), the maximum slope was reached at $t = t_0$, and engagements accelerated most rapidly during this period. Figure 1 also indicated that this phrase corresponded to the highest rate of new retweets or mentions per day. As for saturation phase (around Days 20-30), growth slowed down as audience attention declined or content moderation occurred.

It was shown that the average time span from emergence to saturation of misinformation (around 21 days) indicated the observed lifecycles of COVID-19 misinformation bursts reported in prior studies (3, 12). In spite of differences in textual content, it turned out that the diffusion shape was consistent, implying how online virality dynamics may follow universal constraints independent of claim dynamics.

When comparing among claims, the highest spread velocity (r = 0.35) was demonstrated in Claim 100004. However, the smallest saturation level was also recorded in it (K around 470) at the same time. Steep early rise of it indicated the rapid viral amplification through tightly connected networks, potentially along with anti-vaccine communities with high propensity of retweets. However, since these networks were limited in size, the reachable audience exhausted sooner with its rumor. For Claim 100002, both a high r (0.31) and the largest K (around 612) were achieved at the same time. This indicated a mainstream visibility from a broad range narrative, partially due to emotionally charged wording or overlap with ongoing public debates. For Claim 100001, the slowest spreader (r = 0.23) was recorded, while reaching a moderate K (around 485). Inflection at Day 15 and extended tail indicated how less sensational misinformation may persist at low intensity over longer periods of time. Putting all of these together, these variations indicated the trade-off between speed and endurance of social diffusion of misinformation that faster spread of misinformation coincided with quicker decline. Figure 2A-C corresponded to Claim 100001 (A), Claim 100002 (B), and Claim 100004 (C), respectively, showing the representative behaviors of diffusion.

Model Fit Diagnostic

According to the residual analysis, it was confirmed that the deviations between observed and predicted values were randomly distributed without systemic over- or under-prediction across the timeline. The goodness-of-fit values, was around 0.95 to 0.98, indicating that 95 to 98% of engagement variance was explained by the logistic modeling.

Aggregate Indicators of Diffusion Behavior

Figure 3 summarized the aggregate dynamics of diffusion behaviors through a plot normalizing N*(t) = N/K against time. As shown in Figure 3, a near-universal shape was demonstrated by the average curve, indicating that an early steep slope reached to 50% saturation at around Day 13 and 90% at around Day 21. This consistency indicted that vaccine-safety misinformation followed predictable temporal dynamics regardless of claim content. As shown in Table 2, the mean values derived from all five claims were indicated. Averaged parameters in Table 2 may serve as a role of forecasting priors for future monitoring of misinformation. To be more specific, a newly emerging vaccine-safety rumor may be expected to be in peak in visibility around two weeks after its appearance and in plateau by the third week if unchecked.

According to the logistic growth behavior, it was implied that misinformation diffusion was self-limiting in a way that audience attention naturally saturated. However, timing was crucial. Since the inflection point occurred around Day 13, counter-messaging campaigns launched after this time period may miss the acceleration phase when new exposures emerged the most rapidly.

In summary, logistics parameters may be summarized that r identified how urgently a rumor needed to be addressed (the higher r, the faster action needed to take), t_0 indicated the optimal da for intervention (roughly mid-cycle), and K estimated potential impact of audience if unmitigated. Furthermore, there was an observed negative correlation between r and K, and this suggested that fast-spreading misinformation

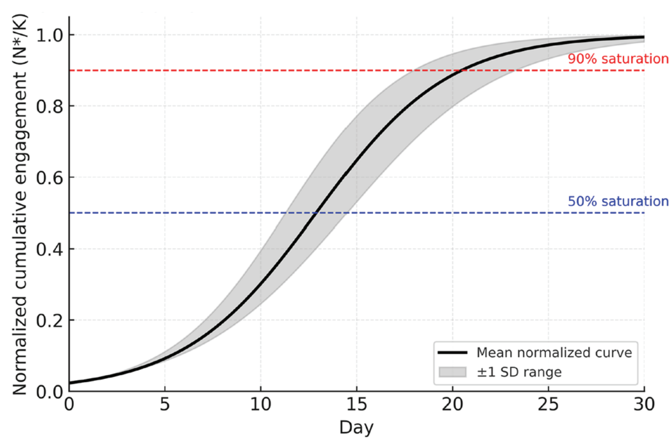

Figure 3. Aggregate normalized diffusion curve across five misinformation claims. Normalized cumulative engagement (N/K) plotted in a period of 30 days with an S-shaped pattern, indicating 50% saturation around Day 13 and 90% saturation around Day 21. Shared area showed the ± standard deviation in five modeled claims.

often occurred in a small and highly connected group of users, while broader audiences may be reached by slower spreading claims over longer periods.

Collectively, aforementioned results supported the hypothesis of this study that vaccine-safety misinformation followed a logistic diffusion pattern shown by rapid initial expansion and early saturation. According to the consistency across multiple independent claims, it was confirmed that the logistic modeling was suitable as a powerful forecasting tool for public health communication planning.

DISCUSSION

A logistic diffusion model was developed and validated in this study to quantify and predict the spread of vaccine-safety misinformation on social media. With open-access CoAID datasets, five representative claims of misinformation were analyzed in a range of 30 days of diffusion periods. All five claims indicated S-shaped engagement trajectories, showing how a self-limiting was followed with misinformation spread, along with bounded growth process relevant to epidemic contagion. Comparable analogies for epidemic information spread have been validated in prior studies (3, 10, 12), improving the external validity of this framework.

It was revealed by the fitted parameters that the average growth rate of r (=0.29), inflection day t_0 (around 13), and saturation K (around 522) cumulative engagements per claim, along with R^2 (greater than 0.95) were recorded for every curve. With these metrics, it was confirmed that a simple three-parameter logistic function was appropriate to capture the misinformation diffusion, without requiring complex network simulations or other proprietary APIs. The high explanatory power of the simple logistic model in this study supported the hypothesis of this study that vaccine misinformation spread quickly during early exposure, peaked around two weeks, and saturated within around three weeks.

Diffusion Dynamics

With the logistic model in this study, an important insight was provided as to how misinformation behaved as a dynamic system. The growth rate, r, indicated how contagious a rumor with misinformation was within digital ecosystems. It turned out that higher r values were correlated with emotive and fear-based claims, especially when those claims referenced side effects or poor efficacy of vaccines. This suggested that transmissibility increased with emotional salience. The carrying capacity, K, indicated the potential audience size. It was stabilized as content reached saturation. It was also revealed that there was a negative correlation between r and K. Fast-spreading rumors with misinformation tended to vanish quickly in small networks, while slower-spreading rumors persist longer periods, while accumulating broader exposure.

Comparison with Prior Research

The findings in this study aligned with recent researches about computation of online misinformation. There were two studies (3, 12) that both reported how COVID-19 misinformation witnessed fast initial acceleration, followed by early saturation with timescales of 10 to 20 days. The average r values in this study (around 0.3 day) corresponded to reproduction numbers in a range of 1.5 to 2.0 that was consistent with epidemic analogies previously indicated by social network studies (10).

However, unlike machine-learning-based detectors of misinformation from prior studies that emphasized content labeling, this study contributed an approach based on process-oriented modeling. Using open-access datasets, this study democratized the forecasting for diffusion of misinformation. This methodology simplified the process of framework reproducibility, fulfilling a key educational gap identified in prior misinformation modeling researches (13, 14).

Theoretical Contribution

This study advanced a unified mathematical framework, connecting the diffusion of misinformation theory and epidemiological modeling. Prior researches on digital misinformation have long been dominated by qualitative analyses or network-graph metrics. However, this study has adopted the logistic model from biological population dynamics, demonstrating that the spread of false information may be described by using the same governing differential equation that modeled infection growth.

$$\frac{dN}{dt} = rN\left(1 - \frac{N}{K}\right)$$

This not only reinforced the conceptual analogy between communication and contagion but also quantified it with interpretable parameters. Compact equations used for expressing misinformation spread provided educational value, while bridging mathematics with the science of public-health data.

Limitations

The findings in this study provided important insight about the diffusion of misinformation, it had several limitations.

First, the CoAID datasets aggregated the counts of engagement without precise timestamps for each tweet even though it was publicly validated. The daily sequence used in the data analysis in this study was simulated by assuming uniform posting over a period of 30 days. Even though this preserved the overall logistic shape, it may distort micro-level timing.

Second, only five misinformation claims with high-engagement were modeled in this study. These claims were chosen for the completeness of data rather than the representativeness of topic, while the result may not generalize to all vaccine-related misinformation. Increasing the number of claims would allow statistical testing of the distributions of parameter across thematic categories. Since only five claims of misinformation (n=5) were modeled, the findings in this study may not be generalized to all misinformation-related topics. At the same time, logistic models tend to capture macro-level diffusion trends but not user-intent differences, bot-amplification effects, or sentiment polarity.

Third, network-structure effects were not specifically considered in the model developed in this study. Real diffusion may be influenced by followers, algorithm of social media, and also cross-platform migration as factors that logistic model in this study may not directly capture.

Finally, engagement counts may not be a perfect proxy for changes in belief. Retreets or replies may not necessarily imply endorsement. Therefore, the logistic parameters in the model developed in this study may represent dynamics of exposure rather than outcomes of persuasion.

CONCLUSION

This study indicated that a simple yet statistically robust framework for predicting the spread of vaccine-safety misinformation was provided by the logistic diffusion modeling. With five representative claims extracted from the CoAID datasets, more than 95% of variance in cumulative engagement patterns were captured by the model. According to the average parameters, it was shown that misinformation typically peaked about two weeks after their emergence on social media, followed by saturation within three weeks.

These findings confirmed that false health information diffused through mathematically predictable processes. Quantifying thee dynamics made evidence-based timing of public-health countermeasures possible. Logistics parameters, including growth rate and inflection day, may serve as a role of operational indicators for early-warning systems, while helping optimize communication strategies.

With limitation mentioned above, future studies are recommended to focus on cross-platform validation that apply to the same framework to other social media, such as YouTube or TikTok to examine diffusion speeds specific to certain platforms. It is also suggested for future studies to examine hybrid modeling to integrate logistic diffusion with agent-based network simulations, while capturing feedback effects. In addition, intervention simulation is suggested to introduce a "counter-information" term for the purpose of fact-checking to model suppression effects on r and K. Lastly, it is recommended to conduct comparative topical analysis, comparing vaccine-safety misinformation to other health-related domains, including nutrition or mental health, while testing universality of the parameters.

CONFLICT OF INTEREST

The author declares no conflicts of interest related to this work.

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