Competing Narratives during Conflicts: Modeling Narrative Diffusion on Telegram in the Russia–Ukraine Conflict

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Abstract. In modern conflict zones, information warfare unfolds alongside physical violence, with digital platforms becoming key battlegrounds for influence. This study investigates how competing narratives, pro-Kremlin and pro-Ukrainian, diffuse through Telegram during the Russia–Ukraine war. Unlike mainstream platforms, Telegram offers minimal moderation and asymmetrical broadcasting, enabling state and non-state actors to rapidly propagate their perspectives. We apply a stance based epidemiological model, SEI_AI_DZ, to capture the spread and competition of opposing stances within a large-scale Telegram dataset. Our model distinguishes between users who adopt or reject each narrative. Through parameter estimation and diffusion analysis, we quantify the narrative reproduction potential (R_0) and highlight key parameters affecting the transmission dynamics.

Keywords: Narrative Diffusion · Telegram · Russia–Ukraine War· Stance Modeling

1 Introduction

The Russia–Ukraine war is unfolding not only on the battlefield but also across digital spaces, with Telegram emerging as a central platform for information warfare. Unlike more regulated social media platforms, Telegram's lack of robust content moderation and its broadcast-style channel structure make it an ideal venue for rapid, large-scale dissemination of both propaganda and counter-narratives [10]. This architecture allows state and non-state actors to shape public perception in near real-time, often without institutional constraints [11]. One prominent tactic leveraged in this space is the "firehose of falsehood," a strategy characterized by high-volume, multi-channel, rapid, and often contradictory messaging that has been frequently attributed to Russian influence operations since 2014 [14,13]. These campaigns are not just about spreading specific disinformation but about undermining trust, amplifying uncertainty, and polarizing public opinion [17,16]. With Telegram's open channels serving both state-aligned and oppositional voices, the Russia–Ukraine conflict presents an ideal testbed for understanding how narratives diffuse, collide, and compete in online social networks. Traditional models of online information diffusion such as SIR, SEIR, or cascade models often treat misinformation as a single transmissible entity. However, this assumption breaks down in polarized environments where multiple narratives are simultaneously competing for attention. To address this, we apply a stance-based epidemiological model (SEI_AI_DZ, which segments infected users into those who agree with a narrative (pro-Kremlin) and those who oppose it (pro-Ukraine)), while also modeling skeptical behaviors. Our study uses a curated dataset of Telegram messages from Russian-language political channels with high follower counts. These channels span both pro-Kremlin and pro-Ukrainian perspectives, enabling us to analyze the temporal and structural dynamics of narrative diffusion. By fitting the SEI_AI_DZ model to this dataset, we explore the effects of transmission rate, stance transition rate, and platform affordances on the basic reproduction number (R_0) of each narrative stance.

RQ1: Can segmenting the infected compartment into competing narrative types enhance the precision of narrative dissemination modeling?

RQ2: What are the key factors driving the basic reproduction number (R_0) in the propagation of narratives on social media?

RQ3: How does the transmission rate (β) influence the spread and amplification of narratives on social media?

2 Literature Review

Social media is a key arena for the spread of diverse content, including news, rumors, misinformation, and competing narratives. However, many studies have relied on superficial metadata (e.g., hashtags, titles) and often examine a single viewpoint, limiting our understanding of complex narrative interactions on these platforms. Mathematical models such as ODEs [3], PDEs [15,4], and SDEs [6,12] as well as knowledge graphs [1] have been widely applied to study information diffusion, viral content, containment strategies, and network-based interventions. Epidemiological models are particularly useful for modeling narrative spread [5]. For instance, the SIR model captures transitions from susceptibility to dissemination and resistance [18]. Recent advances also have focused on identifying diffusion sources and controlling spread. Percolation-based methods enhance source detection and monitoring using minimal observers [8,9], while strategic edge removal helps hinder propagation [7]. Despite such progress, prior models often neglect competing narratives, especially in semi-open spaces like Telegram where both state and grassroots voices operate. This is crucial in geopolitical conflicts like the Russia–Ukraine war, where narrative control shapes perception. We address this gap by applying a stance-aware epidemiological model (SEI_AI_DZ) to model pro-Kremlin vs. pro-Ukrainian narrative diffusion on Telegram. By capturing user stance transitions to agreement and disagreement, our model offers a more nuanced view of narrative competition.

3 Methodology

This section outlines the methodological framework we employed to model the diffusion of competing narratives during the Russia–Ukraine conflict.

3.1 Data Collection

To study narrative diffusion during the Russia–Ukraine war, we collected Telegram messages from high-impact Russian-language political channels, identified via TGStat. We selected channels with over 10,000 subscribers to ensure relevance and influence. A team of native Russian-speaking annotators categorized channels into four groups: Pro-Kremlin (aligned with Kremlin messaging), Anti-Kremlin (critical of the Kremlin), Neutral (non-partisan), and Other (non-political). To validate these labels, non-native annotators cross-checked classifications using Telegram's translation tool, and political science experts assessed a random sample. Annotation reliability was high, with Cohen's kappa scores of $\kappa = 0.97$ (native vs. non-native), $\kappa = 0.87$, and $\kappa = 0.89$ (expert comparisons). From this annotated dataset, we extracted messages from the top five Pro-Kremlin and Pro-Ukraine channels over a 120-day period. The final dataset included the following: 1,120,665 Pro-Kremlin messages (Agree stance) and 3,631,980 Pro-Ukraine messages (Disagree stance). Full details about this data are available in [2].

3.2 SEI_AI_DZ

On social media, users operate in a dynamic environment where they follow, share, and spread narratives. While considering the SEIZ model, initially, users are susceptible—unaware of a narrative but vulnerable to exposure via active spreaders (infected) or disengaged former sharers (skeptics). New users join continuously (i.e., are recruited), while others leave over time (i.e., autonomously exit). Exposure occurs when susceptible users encounter narrative content, typically through social connections or algorithmic promotion. Once exposed, users evaluate the narrative. Some adopt and share it (becoming infected), while others reject or ignore it (becoming skeptics), with transitions governed by narrative persuasiveness and decision rates. Infected users may lose interest or shift views, transitioning into skeptics at a decay rate. Skeptics, however, can re-engage if re-exposed, reflecting the cyclical nature of attention on platforms. These dynamics form the basis of the SEIZ model, capturing how users move between states of susceptibility, exposure, infection, and skepticism. In this study we enhance the classical SEIZ model by splitting the infected compartment $I(t)$ into two: $I_A(t)$ for users supporting a narrative and $I_D(t)$ for those opposing it. This distinction allows for a more realistic representation of narrative competition on social media. The original interaction term $\beta(I + Z)$ becomes $\beta(I_A + I_D + Z)$, shown in Equation (3), reflecting both agreement- and disagreement-based influence. Exposure now leads to either I_A or I_D, based on user stance and governed by parameters m, p, and δ_D. Specifically, $m\psi$ denotes the rate at which exposed users become promoters (I_A), $p\phi$ represents the rate of transition to the dissenting group (I_D), and δ_D and δ_A capture shifts between stances. Equation (3) also introduces γ_A, γ_D, ν_A, and ν_D to model disengagement due to fatigue or moderation, adding realism to the model. In summary, the extended SEI_AI_DZ model (1) separates agreeing from disagreeing users, (2) models stance shifts between narratives, and (3) includes dropout from fatigue or policy actions. This richer structure better reflects user behavior and narrative dynamics in polarized digital environments. The full model is defined as

$$\begin{cases} \frac{dS(t)}{dt} = \mathit{\Pi} - \beta\big(I_A + I_D + Z\big)S(t) - \mu S(t), \\ \frac{dE(t)}{dt} = \beta\big(I_A + I_D + Z\big)S(t) - (1-m)\psi E(t) - (1-p)\psi E(t) - (1-q)\psi E(t) - \mu E(t), \\ \frac{dI_A(t)}{dt} = m\psi E(t) + \delta_D I_D(t) - (\delta_A + \mu + \gamma_A) I_A(t) + \upsilon_A Z(t), \\ \frac{dI_D(t)}{dt} = p\phi E(t) + \delta_A I_A(t) - (\delta_D + \gamma_D + \mu) I_D(t) + \upsilon_D Z(t), \\ \frac{dZ(t)}{dt} = q\psi E(t) + \gamma_A I_A(t) + \gamma_D I_D(t) - (\upsilon_A + \upsilon_D + \mu) Z(t). \end{cases} \tag{1}$$

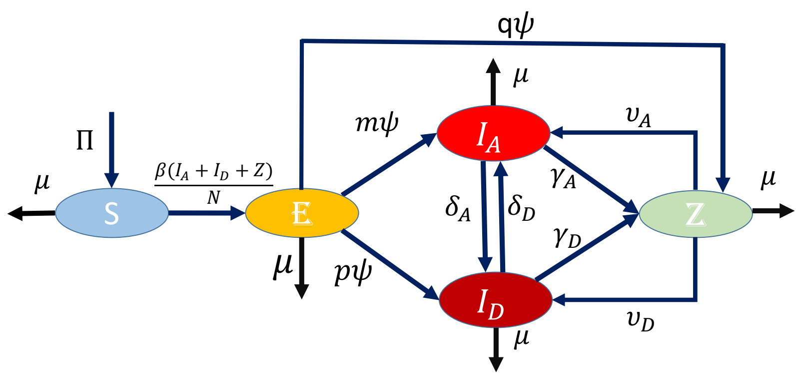


Fig. 1: Transfer diagram of the SEI_AI_DZ model.

Table 1: Interpretation of parameters in the model

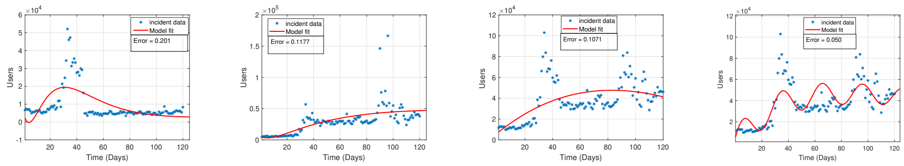
Parameter	Interpretation
Π	Recruitment rate
μ	Autonomous exit
β	Infection rate
ψ	Rate at which exposed individuals transition to the Agreed and Skeptic compartments.
δ_A	The rate at which Agreed revert to Debunk
δ_D	The rate at which Debunk revert to Agreed
m	The proportion of exposed users who transition to the Agreed Infected compartment.
ϕ	Rate at which exposed individuals transition to the Debunk compartment.
p	The proportion of exposed users who transition to the Debunkers compartment, representing those who actively oppose or challenge the narrative.
q	Proportion of exposed users who become Skeptics
γ_A, γ_D	The rate at which Agreed and Debunk revert to Skeptics, respectively
υ_A, υ_D	The rate at which Skeptics revert to Agreed and Debunk, respectively

3.3 Model Fitting and Parameter Estimation

To estimate the parameters of the model equations, we employed the Non-Linear Least Squares Method (NLSM). This method is particularly well-suited for complex systems where the relationships between parameters and observed outcomes are inherently non-linear. The primary objective of NLSM is to minimize the sum of squared differences between the model's predictions and the observed data, thereby ensuring a high degree of accuracy and reliability in the estimated parameters. Initial guesses for the model parameters were made based on prior literature and exploratory data analysis. This approach ensured that the NLSM algorithm began with values within a plausible range, increasing the likelihood of convergence to optimal solutions. The objective function for the Non-Linear Least Squares Method (NLSM) is defined as

$$J = \sum_{i=1}^{n} (y_i - f(x_i;\theta))^2$$

where y_i represents the observed data points, $f(x_i;\theta)$ denotes the model predictions based on the parameter vector θ, x_i are the independent variables, and n is the total number of observations. Now, we present the model fitting and parameter estimates for the discussions surrounding the Pro-Russian and Pro-Ukrainian Narrative. Specifically, Fig. 2a illustrates the parameter fitting for users who posted pro-Russian narratives. In contrast, Fig. 2b presents the model fitting for users who posted pro-Ukrainian narratives. Finally, Fig. 2c and Fig. 2d provide a comparison of the behavior of users holding both perspectives, with the $SEIZ$ model applied to one group and the SEI_AI_DZ model applied to the other, respectively. The final parameter values for the stance-based epidemiological model applied to the dataset are detailed in Table 2.



(a) SEI_AZ (Pro-Ukraine) (b) SEI_DZ (Pro-Russia) (c) $SEIZ$ (Both Narrative) (d) SEI_AI_DZ (Both Narrative)

Fig. 2: Model fitting for Telegram data on pro-Russian and pro-Ukrainian narratives.

Table 2: Estimated parameter values based on Ukraine / Russia war narrative on Telegram dataset.

Parameter	$SEIZ$	SEI_AZ	SEI_DZ	SEI_AI_DZ
Π	100	100	100	100
β	0.11	0.018	0.0046	0.0019
μ	0.0233	0.0021	0.0034	0.0197
ψ	0.47	0.01	0.04	0.001
δ_A		0.21		0.08
δ_D			0.02	0.016
m		0.4		0.09
p	0.001		0.02	0.09
q	0.04	0.008	0.0056	0.04
γ_A, γ_D		0.01, 0.023	0.001, 0.023	0.01, 0.06
υ_A, υ_D		0.01, 0.023	0.1, 0.02	0.03, 0.005

4 Results and Analysis: Russia–Ukraine Case Study

To examine the dissemination of competing narratives during the Russia–Ukraine war, we utilized Telegram data capturing pro-Russian and pro-Ukrainian messaging activity. Our stance-based epidemiological model, SEI_AI_DZ, was fitted to this dataset and evaluated against the baseline $SEIZ$ model. Table 3 shows that for Telegram, the SEI_AI_DZ model achieves the lowest error rate (0.050), indicating superior fit compared to alternative formulations. This directly answers

Table 3: Error rates across models and platforms, demonstrating that the SEI_AI_DZ model outperforms others with the lowest error rate.

Platforms	$SEIZ$	SEI_AZ	SEI_DZ	SEI_AI_DZ
Telegram	0.1071	0.201	0.1177	0.050

RQ.1 for the Telegram data: distinguishing between narrative stances improves the fidelity of information diffusion modeling in conflict zones.

The basic reproduction number $\mathcal{R}_0$ for the SEI_AI_DZ model was computed using the next-generation matrix approach. Fig. 3 illustrates that both transmission rate (β) and decision rate (ψ) significantly impact $\mathcal{R}_0$ for Telegram data. Higher β increases narrative virality, while lower ψ prolongs user indecision, thus amplifying spread, answering **RQ.2**.

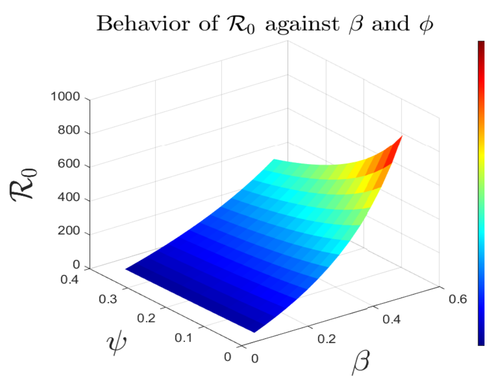


Fig. 3: Effect of $\mathcal{R}_0$ with respect to β and ψ for Ukraine/Russia war narratives on Telegram.

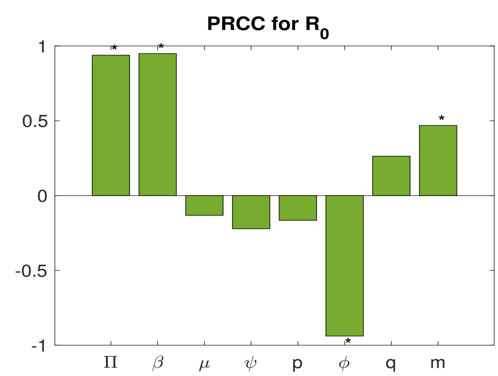
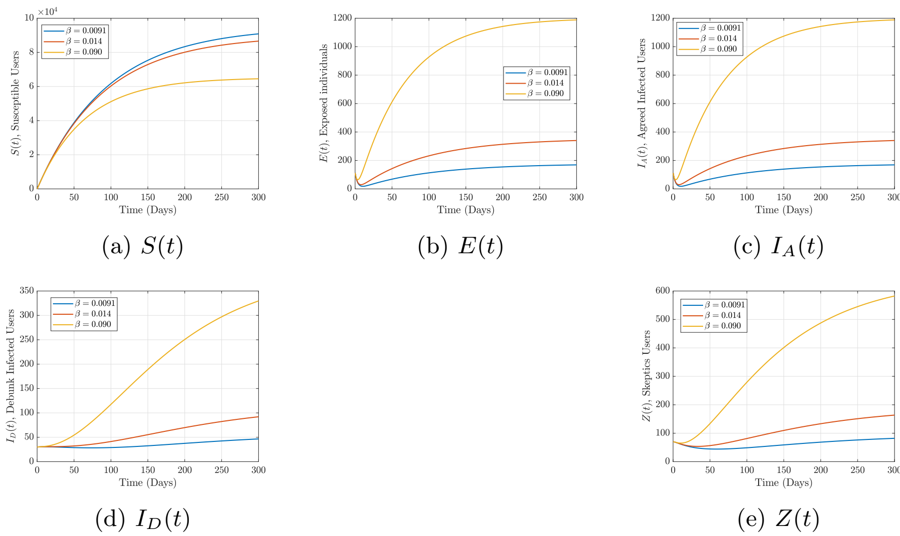


Fig. 4: Sensitivity of $\mathcal{R}_0$ under Ukraine–Russia war narrative Telegram dataset.

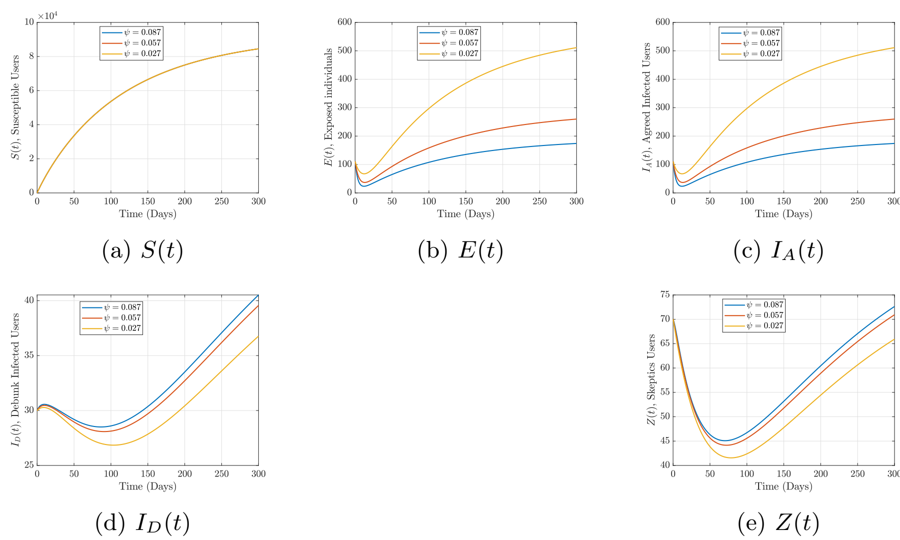
Fig. 4 presents the sensitivity analysis specific to Telegram. The transmission rate β shows the strongest positive correlation with $\mathcal{R}_0$, while user exit rate μ exhibits a strong negative correlation. This supports **RQ.3**, reinforcing that content virality and platform disengagement are pivotal levers in narrative dynamics. To deepen our understanding, we conducted numerical simulations of the Telegram case. We also conducted a sensitivity analysis of the key parameters influencing narrative spread. Figs. 5 and 6 demonstrate that higher values of the transmission rate (β) accelerate the transition from susceptible to exposed and infected states. In contrast, lower values of the stance transition rate (ψ) slow down users' adoption of a stance. Interestingly, the skeptical population (Z) grows under both high β and low ψ, highlighting how increased exposure and delayed decision-making contribute to uncertainty and disengagement in polarized environments.



(a) $S(t)$ (b) $E(t)$ (c) $I_A(t)$

(d) $I_D(t)$ (e) $Z(t)$

Fig. 5: Effect of varying the transmission rate β on the SEI_AI_DZ model using Telegram data.



(a) $S(t)$ (b) $E(t)$ (c) $I_A(t)$

(d) $I_D(t)$ (e) $Z(t)$

Fig. 6: Effect of varying the stance-transition rate ψ on the SEI_AI_DZ model using Telegram data.

5 Conclusion and Future Work

This study applied a stance-based epidemiological model (SEI_AI_DZ) to analyze the spread of competing narratives related to the Russia–Ukraine war on Telegram. By differentiating users into agreeing, disagreeing, and skeptical compartments, the model provided a nuanced view of how pro-Russian and pro-Ukrainian narratives propagate and compete. The results showed that the SEI_AI_DZ model significantly outperformed traditional models (i.e., $SEIZ$), offering a better fit to Telegram data (see Table 3). Sensitivity analysis (Fig. 4b) and reproduction number simulations (Fig. 3b) further identified the transmission rate (β) and transition rate (ψ) as key drivers of narrative amplification. Numerical simulations (Figs. 5 and 6) confirmed that higher β and slower ψ values accelerate and prolong narrative exposure, with skeptics (Z) emerging in later phases due to prolonged engagement. However, limitations remain. The model simplifies user stance as mutually exclusive (agree/disagree/skeptic), which may not capture users holding ambivalent or evolving positions. Future research could enhance this framework by incorporating mixed stances, the influence of external geopolitical events, or user-level psychological traits. Additional longitudinal data could also support dynamic adaptation of parameters. In sum, this work demonstrates that epidemiological modeling—when adapted to digital stance dynamics—can effectively trace the lifecycle of narratives in conflict zones. These insights offer both theoretical contributions and practical tools for policymakers and platforms aiming to manage information warfare in hybrid media environments.

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