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Modeling the Spread of Disinformation Using the SEDPNR Epidemiological Model

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Abstract

This article focuses on modeling the spread of disinformation narratives on social media using the SEDPNR epidemiological model, an extension of the basic SEIR model that takes into account the specifics of digital communication. This includes the existence of a "doubt" phase and the division of active users according to their sentiment polarity. The analyzed data describe a specific disinformation narrative, “Biolabs Ukraine,” that spread in connection with the Russian invasion of Ukraine. The results demonstrate that the dissemination of the narrative exhibits characteristics of an infodemic wave: a rapid increase, a brief peak, and a subsequent decline. The analysis confirms the significant role of active users and shows that supportive and critical reactions both contribute to the further dissemination of content.

KEY WORDS: *disinformation, information warfare, SEDPNR model, epidemiological modeling, social media, sentiment analysis, narrative, infodemic, hybrid conflict*

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1. Introduction

Contemporary armed conflicts are characterized by a highly dynamic information environment, significant polarization, and the widespread dissemination of deliberately manipulative content. The Russia-Ukraine conflict is an example of where traditional war propaganda intersects with the modern social media landscape. In this environment, disinformation does not spread randomly but rather exhibits certain patterns that can be described and modeled using epidemiological tools.

The SEDPNR model extends traditional epidemiological approaches by including states of doubt and disengagement. This allows us to track how users gradually encounter a narrative on a digital network, how they react to it, and whether they actively spread it. By incorporating actual user interactions, such as views, likes, comments, and retweets, the model can reflect the real-world functioning of social networks.

This study analyzes a disinformation narrative that circulated during the Russian invasion of Ukraine (2022–present). Specifically, it examines the claim about the alleged “American biolabs in Ukraine,” which spread through official Russian channels, state media, and social media accounts. Using data obtained from X (formerly known as Twitter) tagged with the hashtag #BiolabsUkraine, we reconstructed the time series of the narrative’s dissemination and estimated the parameters of the SEDPNR model.

This study aims to describe and analyze the dynamics of disinformation narratives, identify key actors and dissemination structures, and evaluate the effectiveness of interventions that limit the spread of harmful content. These results will serve as the basis for proposing effective information defense strategies and practical recommendations for communication and interventions in online environments.

2. Spread of disinformation in the Russia-Ukraine conflict

The spread of disinformation has become a key aspect of the information war surrounding Russia’s February 2022 invasion of Ukraine. This conflict is not only about traditional military combat on the front lines, but also about information warfare [1], which includes coordinated campaigns designed to influence public opinion at home and abroad. Since the

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beginning of the conflict, extensive disinformation efforts have been identified. These efforts aim to undermine trust in official sources of information by casting doubt on the legitimacy of the Ukrainian resistance and portraying Russian actions as justified or inevitable. Russian disinformation campaigns, for example, have vehemently promoted claims about the “denazification” of Ukraine or the protection of the Russian-speaking population, despite these claims being repeatedly debunked by independent fact-checkers [2,3].

Social media platforms have become the primary arena for disseminating these narratives. Channels such as Telegram, X, and Facebook were used to publish false claims, manipulated photos and videos [4], and entirely fabricated content, all of which spread quickly. These campaigns were defined not only by the volume of shared content, but also by sophisticated techniques for targeting various audience groups, including users outside of Russia and Ukraine [5]. In addition to government-sponsored or officially sanctioned activities, there have been sophisticated campaigns that deliberately mimic objective journalism or fact-checking in an effort to legitimize disinformation. One notable example is the platform “War on Fakes,” which poses as a neutral fact-checking source but actually spreads narratives that benefit Russian propaganda and cast doubt on evidence of Russian war crimes.

Research shows that disinformation related to this conflict had a wide reach and real-world impact on public opinion. Analyses of social media revealed that legitimate news and false narratives circulated simultaneously, with some false posts spreading beyond the original conflict and influencing perceptions of security issues in other countries [6]. This information environment must be viewed as part of a broader hybrid conflict in which state and non-state actors seek to influence attitudes, disrupt social bonds, and undermine public trust in objective information by using digital platforms.

The “Biolabs Ukraine” narrative is one of the most significant disinformation campaigns in the information sphere related to the Russian invasion of Ukraine in 2022 [7]. It claims that there is a network of secret biological laboratories in Ukraine funded and controlled by the United States for the development of biological weapons against the Russian Federation. However, these claims have never been substantiated by credible evidence and have been repeatedly refuted by international institutions and independent experts.

Nevertheless, this narrative has become a significant tool in the information war. Its dissemination intensified after Russia’s invasion of Ukraine in February 2022. It was used to justify military operations, delegitimize the Ukrainian government, and discredit the United States and NATO. Public statements and official communications from Russian state institutions—particularly the Ministry of Defense of the Russian Federation—which actively supported the narrative, played a significant role in the initial phase.

Thanks to its open structure, rapid content dissemination, and powerful amplification mechanism via retweets, X (formerly Twitter) played a key role in spreading the “Biolabs Ukraine” narrative. The discussion centered on specific hashtags, primarily #BiolabsUkraine, enabling rapid content aggregation and the formation of thematically connected user communities. Analyses show that a significant proportion of interactions were retweets, suggesting a high level of coordinated content amplification.

Studies focusing on the network structure of how this narrative spread point to a significant asymmetry between the number of active disseminators and the number of users merely exposed to the content. A small number of highly active accounts, often associated with state or pro-Kremlin information sources, created content that was subsequently disseminated on a large scale by a broader user base. This dynamic corresponds to well-known patterns of disinformation spread on social media, in which a relatively small group of initiators and amplifiers of the narrative plays a key role, rather than massively active users [8,9].

In terms of timing, discussion about “Biolabs Ukraine” on X peaked in March 2022, following a typical infodemic curve. There was a rapid initiation phase, sharp increase in activity, brief peak, and subsequent gradual decline. While the narrative persisted throughout the conflict, the most significant wave of dissemination occurred within a relatively short timeframe.

3. Epidemiological models

Epidemiological models are mathematical and conceptual tools designed to describe how infectious diseases spread within a population. The primary goal of these models is to capture the transmission process between individuals, identify key factors that influence the rate and extent of spread, and enable the analysis of possible future scenarios. These models assume that the behavior of population members can be reduced to a limited number of states, between which transitions occur based on defined rules and parameters. As computational methods have developed and large datasets have become available, epidemiological models have gradually expanded to better reflect real-world conditions. Modern approaches consider the structure of contacts within the population, the temporal variability of transmission parameters, and the influence of external interventions, for example.

Although epidemiological models were originally developed to study infectious diseases, the principles behind them can be applied to any process involving the transmission of information, behavior, or influence among network actors. In the context of the digital information environment, the spread of disinformation narratives can be analogized as a process of “infection,” whereby users are gradually exposed to content, react to it, and potentially spread it further [10].

The *SIR model* is one of the most fundamental and historically significant epidemiological models used to describe the spread of infectious diseases in a population. It is the basis for most modern epidemiological approaches. The model categorizes the population into three states: susceptible (S), infected (I), and recovered (R). Susceptible individuals are susceptible to infection, infected individuals are currently infected and capable of transmission, and recovered individuals have recovered and no longer contribute to the spread.

A basic assumption of the SIR model is that the population is homogeneously mixed, meaning every individual has an equal probability of coming into contact with others. Transitions between states are governed by two main parameters: the transmission rate and the recovery rate. These parameters determine the dynamics of the epidemic's spread and enable an analytical study of its peak emergence and subsequent decline.

Despite its simplicity, the SIR model provides valuable insight into the fundamental mechanisms of disease transmission and serves as a widely used reference framework. However, its limitations [11] have led to the development of several extended models that build upon this foundation [12,13,14]. Nevertheless, the SIR model remains a key tool for understanding epidemiological modeling principles and serves as a foundation for constructing more complex models.

The *SEIR model* is an extension of the basic SIR model that includes an additional state: exposed (E). This state represents individuals who have been exposed to the infection but cannot yet transmit it. This state corresponds to the latent or incubation phase of the disease, allowing for a more realistic depiction of temporal spread dynamics, especially for infections with significant delays between infection and infectiousness.

Including the exposed state significantly impacts the model's behavior. Compared to the SIR model, it shifts the timing of the epidemic peak and alters the shape of the infection curve. This effect is crucial when modeling real-world epidemics because the incubation period significantly influences the rate of spread and the effectiveness of potential interventions. Thus, the SEIR model allows for the analysis of situations in which infection spreads covertly within the population without being immediately detectable.

As in the SIR model, the SEIR model assumes homogeneous population mixing. This simplifies the model's mathematical formulation, but it also imposes limitations when applied to complex social systems. Nevertheless, the SEIR model is widely used in epidemiology and disease ecology, where it serves as a compromise between simplicity and realism. The model's structure provides a suitable framework for expansion with additional states or transitions [15,16,17].

In the context of non-biological applications, the status of exposed individuals can be interpreted as a phase of passive exposure to a phenomenon. During this phase, the individual perceives the content but does not disseminate it further. This feature makes the SEIR model particularly suitable for studying the spread of information and disinformation in the digital environment, where there is often a time lag between initial contact with content and active dissemination. Thus, the SEIR model naturally leads to more sophisticated models that capture a broader spectrum of user behavior.

In online discussions, there is not merely "spread" / "does not spread" dichotomy; the formation of opinions and the polarization of attitudes also play significant roles. Users may be uncertain about a narrative, support it, or actively refute it. Paradoxically, both activities contribute to its further visibility. Therefore, to capture these phenomena, it is appropriate to use the extended *SEDPNR model* proposed by Govindankutty and Shynu [18]. This model is a specialized adaptation of the epidemiological approach for the information environment.

The SEDPNR model builds on the SEIR model and adds two key elements. One is the "doubters" state, denoted by D. This state reflects users who have heard the narrative but have an ambivalent attitude and are considering its credibility. State D is an intermediate stage between mere exposure and active participation in the discussion. This state serves as a moderating mechanism, providing a more realistic depiction of individuals' decision-making processes. The other is splitting the infected state (I) into two groups: positively (P) and negatively (N) infected, based on the sentiment of the rumors. Both groups generate content that can lead to greater exposure among susceptible users. Even negative or critical reactions can increase a narrative's visibility and promote its spread. This corresponds to empirical findings on how social networks function, as rumors and fake news typically spread only through strong emotions.

Transitions between states reflect the gradual progression of a user's interaction with disinformation content. Susceptible individuals become exposed as a result of contact with infectious users. Exposed users may transition to the doubting state, accept a narrative with positive or negative sentiment directly, or lose interest and return to their original state. Users in the doubting state may subsequently transition to one of the infectious states or leave the discussion. Individuals in states P and N gradually transition to state R, where they no longer influence the spread. Figure 1 provides a visual representation of the SEDPNR model.

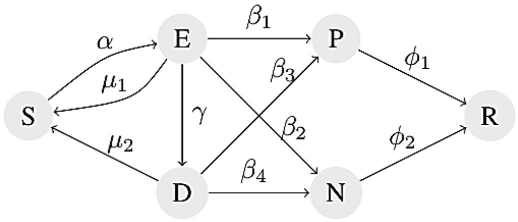

Fig. 1. Visualization of the SEDPNR model

The SEDPNR model is formulated as a deterministic compartmental model with continuous time to quantitatively describe the dynamics of the spread of a disinformation narrative. This model is expressed as a system of nonlinear ordinary differential equations. Each state of the model represents the proportion or number of users currently interacting with the analyzed content in a given phase.

Let the functions $S(t)$, $E(t)$, $D(t)$, $P(t)$, $N(t)$, $R(t)$ denote the sizes of individual state groups at time t. The total population size is considered constant and satisfies the balance equation $S(t) + E(t) + D(t) + P(t) + N(t) + R(t) = N_{\text{tot}}$, where N_{tot} is the total number of users under observation. The model assumes frequency-dependent transmission, which is analogous to epidemiological models of infectious diseases. The probability of exposure is proportional to the number of contacts between susceptible users and infectious individuals. Since positive and negative users can both play an infectious role, transmission is governed by the sum P + N.

The system's dynamics are described by the following system of equations:

$$\begin{aligned}
\frac{dS}{dt} &= -\alpha\frac{S(P+N)}{N_{tot}} + \mu_1 E + \mu_2 D \\
\frac{dE}{dt} &= \alpha\frac{S(P+N)}{N_{tot}} - (\beta_1 + \beta_2 + \gamma + \mu_1)E \\
\frac{dD}{dt} &= \gamma E - (\beta_3 + \beta_4 + \mu_2)D \\
\frac{dP}{dt} &= \beta_1 E + \beta_3 D - \phi_1 P \\
\frac{dN}{dt} &= \beta_2 E + \beta_4 D - \phi_2 N \\
\frac{dR}{dt} &= \phi_1 P + \phi_2 N
\end{aligned} \tag{1}$$

The parameter α describes the intensity with which narratives spread through interactions between infectious and susceptible users. Parameter γ represents the proportion of users who adopt a skeptical or uncertain attitude after exposure. Parameters β_1 to β_4 determine the rate at which exposed and doubtful users engage in active dissemination. Parameters ϕ_1 and ϕ_2 describe the rate of activity decay, or the transition to the restricted state. Return transitions μ_1 and μ_2 are included in the baseline calibration because the natural return of users to a passive state is common in discussion dynamics.

4. Results

The SEDPNR model is used to analyze the spread of a disinformation narrative concerning alleged biological laboratories in Ukraine. This narrative was actively disseminated on platform X in the information space in connection with the Russian invasion of Ukraine. The analysis covers the period from March 1 to 28, 2022. During this time, there was a significant surge in English-language discussion about the so-called "Biolabs Ukraine" on X. This period follows public statements by Russian state institutions, particularly the Russian Ministry of Defense, which promoted this narrative systematically. The analyzed data includes all publicly available English-language posts containing the hashtag #BiolabsUkraine, including original tweets, retweets, and replies.

4.1. Data and their classification

The data collection methodology utilizes standard procedures for analyzing content and information dissemination on X, employing the platform's official application programming interface (API). This approach allows for the systematic, transparent, and reproducible collection of publicly available posts and the necessary metadata for a quantitative analysis of information dissemination.

In this study, a narrative is defined as an interpretive framework that simplifies a complex geopolitical reality and spreads through user interactions on social media. In this case, the narrative is the claim that Ukraine (with the support of the United States) operates secret biological laboratories intended for the development of biological weapons.

The narrative classification system categorizes X posts based on their relationship to an interpretive framework rather than the factual accuracy of individual claims. Content is divided into the following categories:

- Supporting Narrative: posts that reproduce, develop, or reinforce the narrative.
- Neutral mention: posts that merely mention the narrative without an apparent value judgment.
- Counter-narrative: posts that question, criticize, or refute the narrative.

These categories provide an empirical basis for assigning users to states within the SEDPNR model. In the model, states are not determined by the accuracy of the content, but rather by the level of activity and involvement in dissemination of the user. The mapping is performed as follows:

- Neutral or passive mentions correspond to state E (Exposed).
- Hesitant, verifying, or ambiguous reactions correspond to state D (Doubter).
- Active support for the narrative corresponds to state P (Positively infected).

- Active criticism or polemic corresponds to state N (Negatively Infected).

In the model, states P and N are considered infectious, as both types of activity lead to further interactions and increase the narrative's visibility on the network. Thus, even critical or dismissive posts can indirectly contribute to their spread.

Sentiment classification is used as an additional tool to determine the polarity of these active reactions. Three basic categories are identified: positive sentiment, which indicates support for or agreement with the narrative; negative sentiment indicating disagreement with or criticism of the narrative; and neutral sentiment, which reflects an absence of a clear, value-based stance. Sentiment polarity is primarily used to classify infectious users into positive (P) and negative (N) states. Users in E and D states typically exhibit neutral sentiment, as active content dissemination has not yet occurred.

Narrative and sentiment classification serves as an operationalization mechanism that converts observed user behavior into state variables of the model. Automated classification based on artificial intelligence and natural language processing methods was used to assign posts to specific narrative and sentiment categories. This approach aligns with the macroscopic nature of epidemiological modeling, which works with aggregated behavioral patterns rather than individual cognitive processes.

4.2. SEDPNR model

First, the total number of users potentially affected by the analyzed narrative was determined. The next step was the identification of accounts that interacted with the content in a passive manner (exposure), hesitantly (doubt), and actively (sharing the content). Finally, users were divided into individual categories based on narrative and sentiment classification according to the type of interaction. The initial conditions for the model were established based on the aggregated data.

The total population is the estimated number of unique users who were potentially exposed to the narrative in question during the analyzed period. It is an estimate of the number of individuals in the English-speaking audience, $N(0)$ = 8,500,000. State $E(0)$ includes users who have encountered the narrative at least once (e.g., viewed it, mentioned it, liked it, retweeted it, or shared it), but have not yet shared it actively. This corresponds to 2,731,901 users. Doubters are a subset of exposed users who reacted hesitantly or verified information without taking a clear stance. Of the total number of exposed users, $D(0)$ = 412,517 transitioned to the doubter state. Active users are those who began actively sharing or commenting on the content after a phase of doubt. This marks their transition to the infectious state of the model. According to empirical data, 183,653 users reacted in this way. The positively infected group includes users who actively support the narrative — those who post supportive comments, share content, or reinforce the claims. Sentiment analysis showed that this group consists of $P(0)$ = 118,079 users. Negatively infected users criticize or refute the narrative. However, their activity increases its visibility. This approach was observed in $N(0)$ = 65,574 users. At the start of the simulation, users who have already left the discussion are not considered, so the number of restricted users is zero. Susceptible users represent the remaining portion of the population that has not yet been exposed to the narrative. Their number is calculated using the model's balance equation, $S(0) = N_{\text{tot}} - E(0) - D(0) - P(0) - N(0) - R(0)$ = 5,171,929.

The parameters are estimated sequentially. First, the parameter γ and the activity distribution between the positive and negative branches according to the sentiment classification are determined from the time series. Next, the decay parameters, ϕ_1 and ϕ_2, are estimated from the evolution of the P and N states. Then, the parameters β_1 to β_4 are calculated from the state equations for the P and N states using the sentiment classification. Next, the parameter μ_2 is determined. Finally, the parameters α and μ_1 are estimated.

Table 1.

System (1) parameter values

$\alpha = 0.95$	$\beta_1 = 0.125$	$\beta_2 = 0.0695$	$\beta_3 = 0.286$	$\beta_4 = 0.159$
$\gamma = 0.151$	$\mu_1 = 0.044$	$\mu_2 = 0.035$	$\phi_1 = 0.134$	$\phi_2 = 0.166$

The SEDPNR model's system of differential equations was solved numerically. Since the system is nonlinear, an analytical solution is not possible. Therefore, numerical integration with a discrete time step, $\Delta t = 1$, was used. The derivatives were approximated using forward difference, and the explicit Euler method was used for numerical integration. The chosen time step, $\Delta t = 1$ day, corresponds to the temporal resolution of the data. The numerical stability of the model was validated by comparing the results with a reduced time step ($\Delta t = 0.5$), and the discrepancies were found to be negligible.

The model's balance condition was verified. However, the total population, N_{tot}, represents an estimate of the number of users who could have potentially accessed X during the analyzed period. Users for whom contact with the analyzed narrative could not be confirmed (due to inactivity, for example, or a lack of interaction in the data) were included in the S group, i.e., susceptible users.

After calculating the daily values of the parameters from the time series, the final values were determined by taking the arithmetic mean over the entire 28-day observation period. This approach minimizes the impact of short-term fluctuations, providing a stable estimate of the system's long-term behavior [19]. The resulting parameter values are presented in Table 1.

4.3. Interpretation of model parameters

The exposure intensity parameter (α) represents the degree of contact between susceptible users and active disseminators of the narrative. A value of 0.95 indicates high exposure intensity, though not extreme. This corresponds to a situation in which the narrative was prevalent in the online space, yet it did not become fully viral across the entire population. In March 2022, this value can be interpreted as a consequence of the increased media attention related to the war in Ukraine. During this time, the narrative primarily spread through existing information networks but did not reach the entire platform.

The parameters β_1 and β_2, which represent the direct transition from exposure to active propagation, reflect the proportion of exposed users who reacted immediately, without hesitation. A higher value of β_1 (0.125) than β_2 (0.0695) indicates that a supportive reaction is more likely than a critical one. This suggests that some in the audience were predisposed to accept the narrative immediately without verifying it.

The γ parameter indicates that about 15% of users who were exposed to the narrative entered a phase of doubt. This value suggests the existence of a significant group of users who did not immediately react to the narrative, but instead adopted a hesitant or analytical stance. In the context of the analyzed period, this phenomenon can be interpreted as a consequence of increased informational uncertainty, during which some users actively sought additional information.

The sum of the parameters describing the transition from the doubting state to the active states P and N corresponds to the proportion of doubters who engaged in active discussion. The higher value of β_3 (0.286) compared to β_4 (0.159) confirms that supporters of the narrative emerged more frequently from the doubting group than critics did. This effect may be related to algorithmic amplification or the structure of the information communities through which the narrative spread.

The parameters μ_1 and μ_2 represent the proportion of users who left the discussion without participating after being exposed to it or expressing doubt. These relatively low values suggest that most exposed or doubting users ultimately became active participants (even if this only involved clicking “Like”).

Decay parameters represent the rate at which users lose interest in a topic. A higher value of ϕ_2 (0.166) than ϕ_1 (0.134) indicates that critical reactions had a shorter lifespan than support for the narrative. Critical users often react only once (e.g., by posting a comment refuting the claim), whereas supportive activity shows a higher rate of repeated sharing. This difference contributes to the fact that the supportive branch of dissemination exhibits greater inertia.

Thus, the model suggests that the “Biolabs Ukraine” narrative was not a short-lived impulse but rather a temporarily stabilized wave of information. However, it lacked the reproductive potential necessary for long-term sustainability without further external stimulation.

4.4. Visualization

As shown in Figure 2, the spread of a disinformation narrative mirrors the classic progression of an epidemic in many ways. The individual curves illustrate how the narrative gradually enters users’ awareness, how they react to it, and how its spread subsequently winds down.

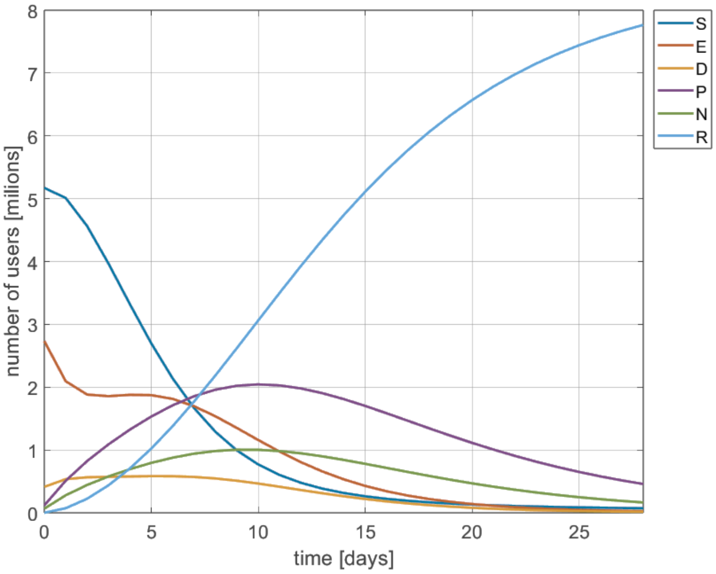

Fig. 2. Dynamics of the SEDPNR model for #BiolabsUkraine

At the beginning of the observation period (the first three days), most of the population is in the susceptible state S. At this stage, the narrative has just been introduced to the information space, so activity related to its dissemination is still relatively low. The first exposed users (E) appear and come into contact with the content, though they do not yet react to it.

Over time, the dynamics change relatively quickly. Between the fourth and tenth day, the number of susceptible users drops significantly while the number of exposed and actively engaged individuals increases. This trend is most evident among positively infected users (P), meaning a portion of the audience quickly accepts the narrative and actively spreads it. At the same time, the number of users who react negatively (N), criticizing or questioning the narrative, also increases. Though they represent an opposing stance, their activity contributes to further dissemination because it keeps the topic visible in the information space. At this stage, a group of skeptical users (D) begins to emerge. Rather than accepting the narrative immediately, they consider it, verify it, or adopt an ambiguous stance toward it. This slows the direct transition to active dissemination and lends the model a more realistic character.

Activity peaks around the tenth day of the observation period. The number of users in the P and N states is highest at this point, reflecting a time when the narrative is most widespread and intensely discussed. The graph also shows that the positive narrative predominates over the negative one throughout the entire period, suggesting that supportive reactions were more widespread and longer-lasting.

Once the peak is reached, activity begins to decline gradually. Starting around day 11, the number of active users is visible in both groups (P and N) begins to decline. The narrative gradually loses momentum, and users begin to drift away from the topic. This trend is reflected by an increase in the number of restrained users (R), i.e. users who are no longer participating in the discussion.

From a longer-term perspective, it is clear that most users have encountered the narrative, but only a small fraction of them have actively engaged with it. This pattern is consistent with how social media typically operates: a relatively small group of active accounts generates content while most users remain passive.

4.5. Contribution to military science

Using the SEDPNR model to represent and assess the spread of disinformation narratives has direct applications in the fields of information and psychological operations. The model provides a quantitative description of narrative diffusion dynamics and identifies key phases in which intervention is most effective.

Within the framework of information operations, the model can detect emerging narratives early and track their development over time. This enables a quick response to growing information threats and the adaptation of communication strategies to the current situation.

In the field of strategic communication, this model helps determine the most appropriate response. The finding that negative reactions can help spread a narrative shows that direct refutation is not always effective. Instead, it may be more appropriate to use indirect communication approaches or focus on a different audience.

For psychological operations, categorizing users into specific groups is essential. The model allows for the identification of the doubters group (D), which is the most suitable for targeted influence. Focusing on this group may be more effective than attempting to change the attitudes of those who are already convinced.

The model can also simulate the impact of measures such as limiting the reach of disinformation sources or introducing a counter-narrative. Adjusting the model’s parameters enables us to estimate the potential impact of individual interventions on the dissemination process.

5. Conclusions

In this study, we analyzed the dynamics of a disinformation narrative spreading on social media and tested the applicability of the SEDPNR epidemiological model to describe this process. The extended SEDPNR model framework allows us to model the speed at which a narrative spreads, the processes of attitude formation and discourse polarization, and the gradual fading of an information campaign. Thus, this model provides a suitable theoretical framework for quantitatively analyzing the dynamics of disinformation operations on social media.

Through a theoretical analysis and subsequent application of the model to real-world data, we identified the key mechanisms underlying the narrative’s spread and its temporal evolution. The results show that the spread of a disinformation narrative follows a typical infodemic pattern: a rapid increase in activity that reaches a peak and then subsides. The SEDPNR model has proven to be a useful tool for capturing both the spread and the process of user attitude formation, including the phase of doubt and the distinction between supportive and critical reactions.

Further analysis confirmed that dissemination dynamics are influenced by both the number of active disseminators and the structure of interactions among users. A key finding is that negative reactions can contribute to furthering the spread of the narrative, which has significant implications for designing communication strategies.

Overall, the spread of the “Biolabs Ukraine” narrative took the form of an intense but short-lived wave of information. A rapid surge was followed by a quick decline, suggesting that, without external support, the narrative lacked the potential to sustain itself in the information space long term. However, it would be simplistic to assume that the narrative has disappeared entirely or that no one believes it anymore. Similar information constructs tend to persist in various modified forms even after the main wave of dissemination subsides.

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