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Roman Romaniuk[1], Oleksandr Voitko[2], Liubomyr Parkhuts[3], Volodymyr Rakhimov[2], Maryna Kostiak[3]

[1] Ukrainian Land Forces Command, Kyiv, Ukraine
[2] National Defence University of Ukraine, Kyiv, Ukraine
[3] Lviv Polytechnic National University, Lviv, Ukraine

MODELS FOR PREDICTING CHANGES IN PUBLIC OPINION DURING THE IMPLEMENTATION OF THE NARRATIVE IN SOCIAL MEDIA

Abstract. Relevance. In the modern world, social media are becoming the main channels of communication, which significantly affects the formation of public opinion and the implementation of strategic narratives. In the context of global information challenges, in particular war, understanding and predicting changes in public sentiment is extremely important for the effective implementation of state information policy, as well as for combating disinformation. **The subject of the study** is modeling the processes of predicting changes in public opinion during the implementation of a strategic narrative through social media. **The aim of the study** is to analyze the effectiveness of using diffusion of innovations models and neural networks to predict changes in socio-political sentiment, as well as to optimize content strategy on social media platforms. **Main results:** The study showed that social media has a significant impact on public consciousness, and the use of information dissemination models, such as Bass's diffusion of innovations model, allows predicting the spread of narratives among different groups of users. The use of neural networks to analyze socio-political sentiment provided highly accurate forecasts with good quality indicators. The results of the study emphasize the importance of adapting content strategy in social media to increase the effectiveness of influencing the audience. **Conclusion**. The results obtained confirm that for the successful implementation of the state's strategic narrative, it is necessary to apply combined methods of forecasting and adapting content on social platforms. Successful adaptation of content strategy, taking into account changes in user behavior and trends in socio-political sentiment, is a key factor for effective influence on public opinion and support of national interests in the digital environment.

Keywords: public opinion; social media; strategic communications; diffusion of innovations; Bass model; neural networks; disinformation; forecasting; content strategy.

Introduction

The strategic course of the state is directly established and implemented by the military-political leadership and the communication potential of the strategic communications system.

It is extremely important for national authorities and civil society to understand the specifics of media consumption by different audiences. Any policy to combat disinformation, attempts to spread true news, and official appeals will be ineffective if it is not implemented on platforms where society actually consumes information. In addition, the Ukrainian authorities need to assess the consequences of their actions (in particular, monopolization of television, content) in the media space in order to promptly respond to the challenges posed by the information war with the russian federation.

The number of people using the Internet daily is steadily increasing every year. In 2023, this figure reached 89%, and among people aged 18-35, 98% reported daily Internet use, with 87% of respondents using smartphones to consume news, and among young people aged 18-35, this figure is 97%.

The most popular news sources have the highest level of trust – about 60% of respondents trust news on social networks, about half trust online news and TV news.

Unlike at the beginning of the war, when users followed the news 24/7, there is now a significant decrease in the frequency of news consumption. Users are gradually returning to everyday worries related to personal life, to the permanent job they lost at the beginning of the war, the situation on the front has more or less stabilized and there is confidence that “Ukraine will win”. On average, users spend 2-3 hours per day watching the news.

The growing role of social media indicates that one-sided receipt of information is gradually losing interest, and feedback, which allows for live communication (likes, comments, reposts), adds efficiency to the creation and distribution of quality content. Social networks have become a reliable platform for the strategic communications system in the implementation and implementation of the strategic narrative, which directly affects the implementation of the state's strategic course and contributes to the protection of national interests in the military sphere by the system of ensuring the state's military security.

The main device through which users receive information is a smartphone, and the main source of news is Telegram channels. In addition, other social networks, various sources on YouTube (TV channels broadcast via YouTube, personal channels of opinion leaders/experts), as well as online news sites are used.

It should also be noted that fighters on the first line of defense do not have the opportunity to consume news daily, as they perform combat missions and keep all devices turned off. In this case, news consumption occurs only after their return (after 1-8 days). Soldiers in the rear have constant access to news and consume it daily. The most popular gadget for receiving news is a smartphone. On the first line of defense, there are no difficulties with accessing news thanks to Starlink and mobile Internet, which is available even in half-destroyed villages. In second place are laptops/tablets, which are often used to perform military missions and to watch news after work. For many soldiers, an important source of information is the commander or the press service of their unit/battalion, if any.

Given the above, we can clearly determine the dependence of the growing role of social networks on the development of information and telecommunications technologies and the development of a strategic communications system that promotes feedback with target audiences (users) on the network (Fig. 1), as well as the gradual decline in the role of television in these processes (Fig. 2).

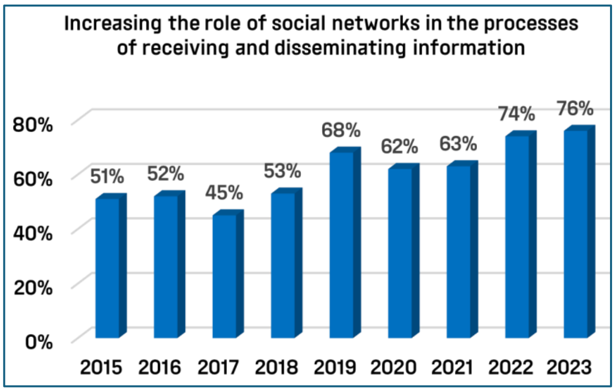

Fig. 1. Growth of demand for social networks

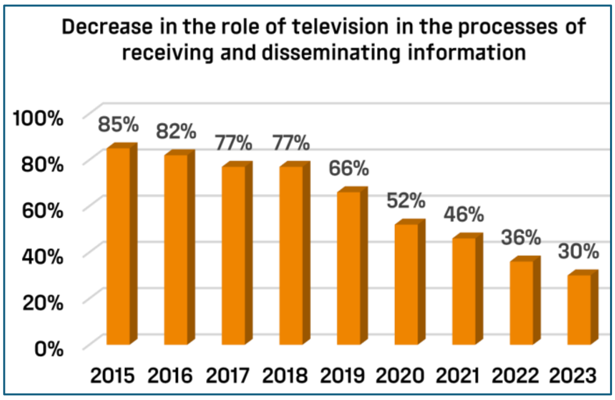

Fig. 2. Reducing demand for television

Literature review. A significant amount of research has been devoted to the issue of predicting the impact on public opinion through social media.

In [1], an analysis of the impact of public opinion and media perceptions on political participation was conducted. However, this approach has limitations in predictability: the results are based on the 2011 protests in Israel, which makes it difficult to generalize to other contexts. Self-reporting by respondents may distort the real picture of the impact of public opinion. The use of surveys and experiments does not completely exclude the influence of external factors. Limited consideration of alternative factors, such as socio-economic status, which may also affect political behavior. These aspects make it difficult to accurately predict the role of the media in shaping public opinion.

The study [2] analyzed how political discourse on social media affects public perceptions of democracy, using data from 11 European countries. It uses a top-down approach that links politicians' statements with citizens' democratic sentiments. The methodology includes text data analysis (word embedding classification) and a survey of the 10th round of the European Social Survey. It found that the coherence between politicians' rhetoric and public perceptions of democracy varies across countries, and the impact of political discourse depends on citizens' political orientation. However, predicting the impact of such discourse has limitations. The established relationship is correlational, not causal, which makes it difficult to determine the direct impact of political statements on public opinion. Algorithmic text analysis may not take into account the context and tone of statements. Citizens may interpret political messages differently depending on their own biases. This means that while the study helps to understand the mechanisms by which politicians influence public opinion, its ability to make accurate predictions remains limited.

The work [3] proposes a new kinetic mathematical model for analyzing the dynamics of opinions in social networks, in particular on the Twitter platform. The model takes into account the role of social contacts and influential individuals who can direct collective opinion. Using real data, the authors calibrate the model, which allows describing the processes of opinion dissemination, polarization and consensus formation in the online environment. However, predictions of the impact on public opinion have limitations. A model based only on Twitter data may not reflect the full picture in other social networks or real social contexts. In addition, kinetic models may simplify complex social interactions, and the prediction of impact may be inaccurate because psychological or emotional factors are not taken into account.

[4] investigates the use of social media data for prediction using machine learning models that combine survey and social media data. The results show that combining previous approval ratings and social media data yields better prediction accuracy than using social media alone. Models based solely on social media are less effective, although they can be useful in cases where agents actively interact with platforms. Predicting public opinion using social media has limitations. Models may be inaccurate if agents are not active on social media or if social media data is not representative. Furthermore, such predictions may be context-specific, where social media activity is a determining factor, making them less effective in other situations.

The paper [5] examines citizens' perceptions of journalists' use of social media data to shape public opinion, indicating that the majority considers the use of aggregated rather than identifiable data to be ethical. It is found that those who are more active users of social media are more likely to support such use of data, and political messages on social media increase the willingness to adopt this new journalistic practice. Predicting the impact on public opinion shows that the use of social media to shape public opinion can be effective, but its acceptability depends on how journalists ensure the ethics of the process. Citizens who are active users of social media are more likely to have a positive attitude, but the majority still require anonymity and caution in data processing, which is important for further predicting their attitudes towards this practice.

The work [6] proposes a new model HFN-BeatsConv, based on improved N-Beats, which uses 3D-TCN for modal alignment of multimodal data from social networks for public opinion prediction. The model processes multidimensional time series data, in particular text messages, taking into account the time of publications, which improves the accuracy of predictions compared to traditional unimodal approaches. In addition, the study includes the use of social media data as an additional source for convenience and robustness of predictions. However, there are several potential drawbacks of the proposed approach. The model requires large amounts of data to achieve high prediction accuracy, which can be difficult in real-world settings where data may be incomplete or noisy. Although multimodal approaches promise more accurate results, they can be difficult to implement and require large computational resources, which limits their application in real-world settings.

The study [7] examines the relationship between the sentiment of corporate earnings reports and subsequent negative sentiment in news publications. Using the FinBERT sentiment analysis model, the researchers analyzed the calls of 30 S&P 500 companies over the period 2012 to 2022 to examine the impact of negative sentiment on news content and market reaction. The results showed a strong correlation between negative sentiment in reports and negative sentiment in news, as well as a multiplicative effect on stock returns when these sentiments coincide. The limited sample size (30 companies) and the use of a single sentiment analysis model (FinBERT) raise issues, which require further research with other methods and larger samples to more accurately predict the impact on public opinion and the market.

The study [8] examines the use of social media data, particularly Twitter (now X), to estimate public opinion using network analysis and machine learning. The Variation Autoencoder (VAE) model is applied to estimate individual political views based on users' network relationships, studying 276,008 German Twitter users. The results of this model are compared with traditional linear models and found that VAE provides more accurate predictions of political preferences and voting intentions, and also better reflects the structure of the social network. This confirms the need for advanced approaches to understand the complex relationships in social networks, especially outside the United States. The article emphasizes the importance of using sophisticated analytical tools, such as machine learning, to predict public opinion based on social network data. The main advantage of the proposed model is its ability to better account for the network relationships between users and their views on political topics. However, one of the drawbacks of this approach is the potential dependence on data quality and the difficulty of interpreting the results, which can affect the accuracy of predictions. In addition, studying only German users limits the generalizability of the results to other regions and cultures.

In [9], an approach to predicting social relationships in networks is described, using a multidimensional model that takes into account not only structural information about users, but also public opinion factors, such as professional environment, interests in opinions and topics, social psychology, etc. The authors developed a forecasting algorithm that combines these multidimensional factors and uses public opinion data from the Weibo platform. The algorithm demonstrated higher efficiency compared to basic methods, in particular, such as the common neighborhood model, the Jacquard index, and the SimRank method. Special attention is paid to how different elements of public opinion affect the accuracy of predicting connections between users and network nodes. The research methodology is based on combining multidimensional network links and analyzing social and psychological factors. Empirical results show that the element of the professional environment of users has the greatest impact on the accuracy of prediction, which significantly improves the effectiveness of the model. At the same time, the element of social psychology has a negative impact on the accuracy of the forecast, which indicates the complexity of integrating psychological aspects into the forecasting of social relations. However, despite the high accuracy of the algorithm, it is important to note that its success depends significantly on the quality and completeness of public opinion data, which may limit the general applicability of the model in conditions with incomplete or unclear data.

In [10], a new algorithm, Fusing Dynamics Equation-Large Language Model (FDE-LLM), is proposed, which combines the dynamics of users' opinions in social networks with epidemic modeling systems using Cellular Automata (CA) and SIR models. The algorithm classifies users into opinion leaders and followers, which allows for accurate prediction of changes in public opinion. The model combines the capabilities of large language models (LLM) with epidemiological models, providing an effective representation of social network interactions and more accurate predictions. The results of the study show that FDE-LLM outperforms traditional prediction methods, demonstrating higher accuracy and interpretability. However, using data only from Weibo limits the generalizability of the results.

Thus, the problem of predicting the impact on public opinion through social media remains relevant and promising.

Purpose and objectives of the study. The purpose of the study is to analyze and model the process of predicting changes in public opinion in the context of implementing a strategic narrative through social media, in particular using diffusion models and neural networks, to increase the effectiveness of the content strategy of state bodies in combating disinformation and strengthening national security.

Research objectives:

Analysis of statistical data on changes in public opinion in the context of news consumption through social media; assessment of the role of social media in the implementation of strategic narratives and their impact on public consciousness.

Modeling the processes of information dissemination and disinformation using the Bass model of diffusion of innovations.

Application of architecture (LSTM – Long short-term memory) to predict changes in socio-political sentiments of the population.

Determination of recommendations for adapting content strategy in social media to increase its effectiveness.

Main part

1. Information/disinformation dissemination models. Rumor dissemination models are used to analyze and simulate information transmission processes in social networks, groups, or other environments of socio-cyberphysical systems.

The main models of information dissemination are shown in Fig. 3. The analysis of Fig. 3 showed that the Daley-Kendall Model is based on three groups [11]:

Ignorants – people who do not yet know the rumor.

Spreaders – people who know the rumor and actively pass it on to others.

Stiflers – those who already know the rumor but do not spread it further (perhaps due to loss of interest or because they received it from several people).

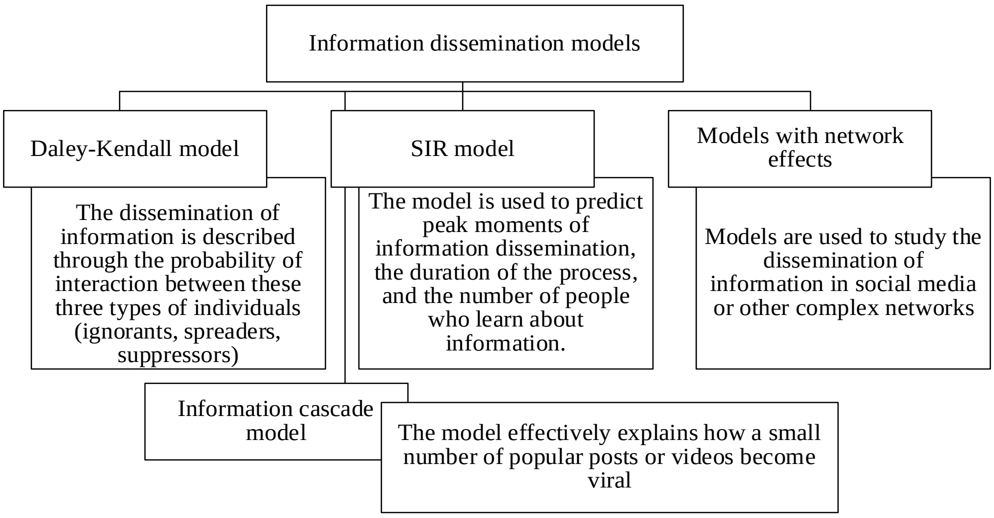

Fig. 3. Main models of information dissemination

The dissemination of a rumor is described in terms of the probability of interaction between these three types of individuals. The transition from ignorant to disseminator occurs when an ignorant encounters a disseminator, who is “infected” with information. Disseminators become deterrents when they encounter other disseminators or deterrents. The model is used to analyze the speed of information (rumors) spread in large social groups. As a rule, additional groups are formed in socio-cyberphysical systems and media resources.

The SIR model (Susceptible-Infectious-Recovered) was originally created for modeling epidemics, but it has been adapted to modeling the spread of information (rumors) [12], due to the avalanche effect of spread. The following groups are used in the model [12]:

Susceptible (S) – people who can be “infected” with the information (i.e. do not yet know it).

Infectious (I) – people who are actively spreading the information.

Recovered (R) – people who are no longer spreading the information.

The model is mathematically described by a system of differential equations that takes into account the change in the number of people in each state:

$$\frac{dS}{dt} = \beta SI, \tag{1}$$

where β is probability of information transmission;

$$\frac{dI}{dt} = \beta SI - \gamma I, \tag{2}$$

where γ is"recovery" speed;

$$\frac{dR}{dt} = \gamma I. \tag{3}$$

The model is useful for predicting peak moments of information dissemination, the duration of the process, and the number of people who learn the information (rumor).

Network effect models consider the structure of relationships between people, such as social networks [13]. A graph is used to represent a system, where nodes are people and edges are the relationships between them.

Networks can be random (Erdès-Rényi), scalable (Barabási-Albert), or small-world (Watts-Strogatz) [13].

Information dissemination depends on the topology of the network: for example, nodes with a large number of connections ("hubs") play a key role. Such models are used to study information dissemination in social media or other complex networks.

In the information cascade model, a cascade is formed when people make decisions to disseminate information based on the actions of others, rather than their own knowledge or analysis [14].

This model is suitable for explaining the viral spread of information on social networks. Early followers (“early adapters”) and the popularity of content play an important role [14]. The model effectively explains how a small number of popular posts or videos become viral.

However, standard methods cannot always be used for forecasting in individual cases. Expert methods are often used to determine interactions in social networks

[22]. However, to obtain substantiated predictive data for assessing the effectiveness of implementing narratives in social media, it is advisable to use quantitative analysis methods.

2. Peculiarities of the mathematical model of innovation diffusion. One of the popular tools for researching public sentiment and information dissemination is Bass's model of diffusion of innovations.

The purpose of the diffusion model is to operationalize the sequential increase in the number of users who have adopted an information product and to predict the further development of the diffusion process that is already underway. In the context of innovative products, diffusion models focus on the development of the life cycle curve and serve to predict the spread of narratives upon first exposure. That is, in models of first-time diffusion of a narrative, it is assumed that there are no repeat users.

The main impetus for the study of diffusion is the Bass model. Bass's model assumes that potential users of innovations (information products) are influenced by two means of communication - the media and radio, which are directly key channels of communication in a social network, where radio can also be considered as chat rooms or social networks. network messengers. In his development, he further assumes that those who have adopted the innovation consist of two groups. One group is influenced only by media communication (external influence), and the other group is influenced only by oral communication, personal communication (internal influence). The first group Bass called "innovators", and the second - "imitators" [15].

Let there be some social network in which a fundamentally new information product appears, which has no analogues and, accordingly, competition from other information products (narratives). This information product creates a new demand, that is, a certain number of users appears who wish to distribute this information product or have already perceived it. Then the number of users who carry out the perception process at time t is described by

$$\frac{u(t)}{1-U(t)} = \alpha + bU(t), \quad (4)$$

where $u(t)$ – probability density function of a random variable t – time of acceptance of new information (speed of perception of the information product);

$U(t)$ – the proportion of users who have adopted the information product by the time point t or, in other words, the time distribution function of users;

a – innovation coefficient or external influence coefficient;

b – imitation coefficient or internal influence coefficient.

The model assumes that each process of information perception occurs either under the influence of advertising and the media (this category of users is called innovators), or under the influence of the opinion of people who have already perceived the information product and disseminated it (this category of users is called imitators). Thus, the probability of perceiving an information product (the left part of (4) depends, firstly, on the external influence (advertising, media), which is assumed to be constant and expressed by the coefficient of external influence; secondly, it depends on the influence of the social system itself, which increases with the growth of the number of users who have already perceived the information product and disseminated it (this influence is assumed to be proportional (the coefficient of internal influence) to this number).

If v – the total potential of users in a social network (a parameter that determines all potential users of the network who can receive and perceive an information product over time, then we will represent *L(t)* as the speed or degree of dissemination (exchange) of an information product at a given point in time t on the social network platform and *W(t)* as the total volume of distribution or dissemination of an information product up to a point in time t on a social network platform (the number of users who perceive an information product at a certain point in time).

Then we get the general form of the equation

$$L(t) = vU(t). \quad (5)$$

Using (4) and (5) we obtain

$$L(t) = av + (b-a)vU(t) - vb(U(t))^2; \quad (6)$$

$$L(t) = av + (b-a)W(t) - \frac{b}{v}W(t)^2. \quad (7)$$

In case if $W(t=t_0=0)=0$, The function of the number of users who have accepted an information product at a certain point in time has the following form

$$W(t) = v\left[\left(1-e^{-(a+b)t}\right)\Big/\left(1+\frac{b}{a}e^{-(a+b)t}\right)\right]. \quad (8)$$

Then we represent the speed of perception of an information product as

$$L(t) = v\left[\frac{a(a+b)^2 e^{-(a+b)t}}{(a+be^{-(a+b)t})^2}\right]. \quad (9)$$

The graph of the growth of the number of users who have already adopted an information product shows that initially the growth rate increases until a certain point in time T^* (inflection point), and then the growth rate begins to decrease. As a result, there is a process of information saturation to level v, i.e. the social network exhausts its potential.

Inflection point T^* is calculated by the formula

$$T^* = -\frac{1}{a+b}\log\left(\frac{a}{b}\right). \quad (10)$$

Knowing the model parameters a and b, from the equation (10), can be calculated the model's intersection point, that is, the actual point in time when the “late majority” will start using the information product in the social network.

So, taking into account the above, let's move on to mathematical modeling to predict changes in public opinion and identify ways to improve the Bass diffusion model.

3. Mathematical modeling of the parameters of the Bass diffusion model for predicting changes in public opinion based on statistical data. To calculate the parameters a, b in the Bass diffusion model based on statistical data, we will consider two examples for obtaining the values of these parameters, which will be based on the coverage of users by the social network (increase in the number of new users) of the YouTube channel “Army TV – Military Television of Ukraine” from February 2021 to January 2024 [16] and the studied changes in the socio-political mood of the population from July 2010 to February 2024 [17]. Let's consider the first example and conduct a mathematical modeling of user reach by a social network. To calculate the parameters a, b in the table 1, we will enter statistical data on the increase in subscribers of the social network "Army TV – Military Television of Ukraine" in the specified period.

Table 1 – **Statistical data on the increase in subscribers to the social network Army TV – Military Television of Ukraine**

#	Month, year	Number of subscribers	#	Month, year	Number of subscribers	#	Month, year	Number of subscribers
1	02.2021	156000	13	02.2022	219000	25	02.2023	790000
2	03.2021	166000	14	03.2022	515000	26	03.2023	797000
3	04.2021	175000	15	04.2022	683000	27	04.2023	797000
4	05.2021	187000	16	05.2022	720000	28	05.2023	800000
5	06.2021	191000	17	06.2022	739000	29	06.2023	803000
6	07.2021	194000	18	07.2022	748000	30	07.2023	810000
7	08.2021	197000	19	08.2022	758000	31	08.2023	811000
8	09.2021	200000	20	09.2022	769000	32	09.2023	814000
9	10.2021	205000	21	10.2022	773000	33	10.2023	817000
10	11.2021	209000	22	11.2022	779000	34	11.2023	817000
11	12.2021	213000	23	12.2022	787000	35	12.2023	817000
12	01.2022	214000	24	01.2023	788000	36	01.2024	837000

To get the value of the parameters *a, b*. We will use the Nelder-Mead optimization method, which is implemented in the minimize function of the scipy.optimize module. This method minimizes an objective function defined as the sum of the squares of the differences between the observed data points and the values predicted by the Bass diffusion model for a given set of parameters *a, b*.

The optimization process iteratively adjusts the parameters until it finds values that minimize the objective function, thus providing optimized values. *a, b* which best fit the data according to the Bass diffusion model.

After optimization with statistical data according to the Bass diffusion model, we obtain the values of the coefficients $a = 0{,}00855$, $b = 0{,}304458$, as well as a graphical representation of the simulation (Fig. 4).

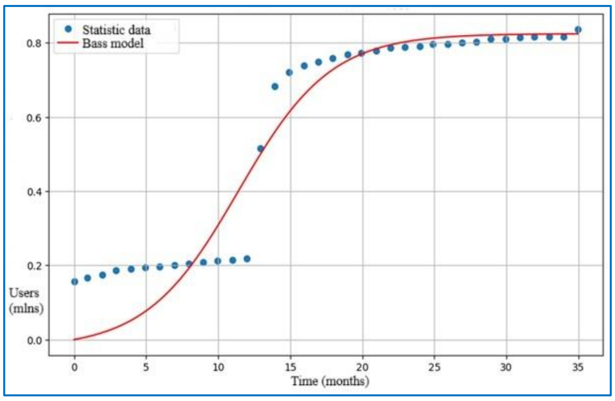

Fig. 4. Optimization of statistical data to the Bass model diffusion curve

High indicators a, b indicate a high level of external and internal influences when joining a specific network, and also indicate that the Bass diffusion model can be practically applied when determining the reach of the target audience by the indicator – “new users joining the network”. As the next example, we will consider a change in the socio-political mood of the population and conduct mathematical modeling based on certain statistical data. Fig. 5 shows statistical data on changes in the socio-political mood of the population. To simplify calculations, we will take the data for December 2022 as the population of Ukraine, which will be a constant – 41 310 400 [17].

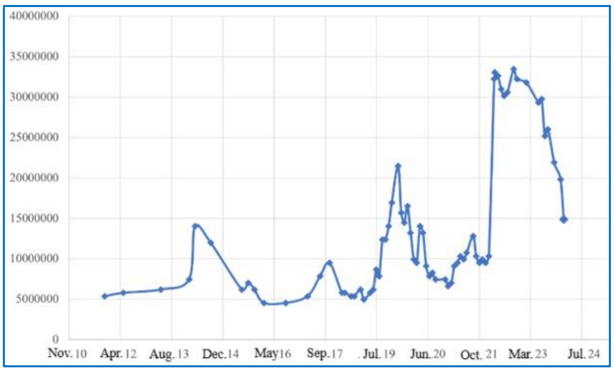

Fig. 5. Socio-political mood of the population

So, after modeling using statistical data, we obtain the following data for the Bass diffusion model: $a = 0{,}000163$ (external influence coefficient), $b = 0{,}0163$ (internal influence coefficient) and we will obtain a graphical representation of the diffusion curve fitted to statistical data (Fig. 6).

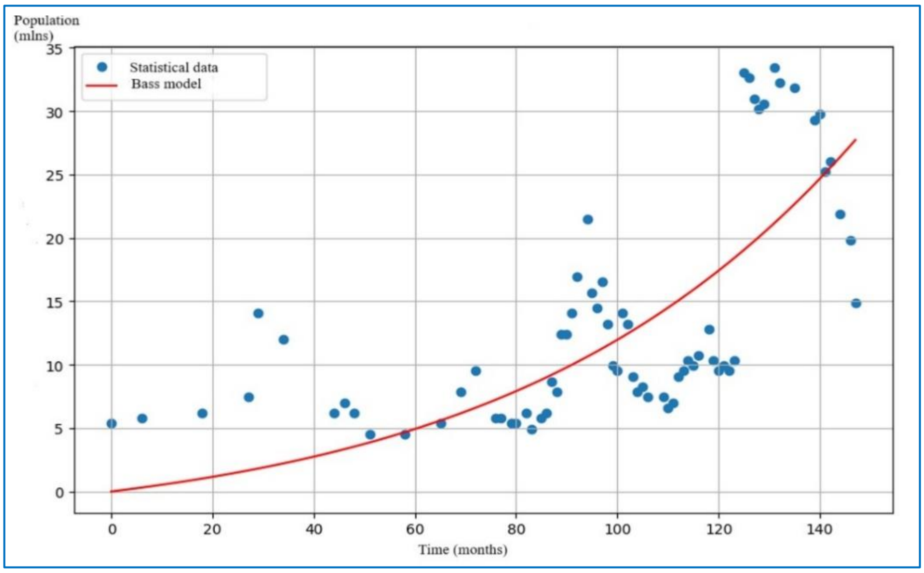

Fig. 6. Optimization of statistical data to the Bass diffusion model curve

This example demonstrates that the diffusion of sentiment proceeded more slowly and did not have a significant jump as in the example of joining the network. Knowing the coefficient of external influence and the coefficient of internal influence, we can determine the time when the information product will begin to be used by the “late majority”, which will indicate information saturation in the process of information activities, so we substitute the values of a and b into equation (10)

$$T^* = -\frac{1}{0.000163 + 0.0163}\log\left(\frac{0.000163}{0.0163}\right) \approx 280 .$$

The result obtained indicates that in approximately 23 years and one month the “late majority” will begin to use information products after they are released on social networks. Considering our statistical data for 143 months, we can assume and make a forecast that in 137 months we will receive the maximum number of positive sentiments regarding the socio-political situation in the state. This indicates a low level of awareness and awareness of the population, that is, a low effectiveness of information activities during the conduct of information companies (operations).

The above approaches provide a general idea of obtaining coefficients of external influence and internal influence from statistical data for further forecasting of changes in public opinion. There is a need to investigate the Bass diffusion model for assessing the effectiveness of information measures when conducting an information operation for a specific purpose.

Next, we will carry out mathematical modeling for a specifically defined goal of information activities during the information operation, namely “Within a year, increase awareness by 5% of the population regarding security guarantees and peaceful settlement of armed aggression after joining NATO.”

Thus, to achieve the specified goal, the potential number of users who may change their minds towards support for NATO accession will consist of the target audiences “Hard to answer” and “I will not vote” (v = 892474). The specified indicator for achieving the goal of information activities during the information operation will be 202835 (coverage of public awareness). According to mathematical modeling and taking into account 5% increase in positive attitude per year, to fully reach the target audience, we will need four years and three months, i.e. 1546 days (maximum saturation of the social network with information, which corresponds to the potential of the target audience on the network). The simulated parameters of external and internal influences have the following values: a = 0.000161 and b = 0.0034992. Forecasting the change in public opinion after mathematical modeling for 364 days showed that there were 107,549 more supporters and indicated discrepancies with the specified goal of the information operation almost twice (information activities during the information operation in accordance with the set goal were only 50%). To achieve the specified goal in accordance with the modeling according to the specified diffusion parameters, it is necessary to increase the time for conducting information activities during the information operation, namely from 364 days to 518 days to meet our needs. Therefore, taking into account the ambitious intentions and goal of the operation, we will conduct modeling to achieve the specified goal. The figure shows a comparison of the basic model based on statistical data and the model that implements the achievement of the goal of the operation.

The defined reference points in Fig. 7 correspond to changes in public opinion over time, namely t_{90}, t_{180}, t_{270}, that is, they should correspond to the terms of conducting the focus group survey, which makes it possible to assume that after the survey, positive moods and changes in public opinion should be within the limits of the obtained indicators, namely, correspond to the achievement of the goal of information measures during the information operation. Thus, in further studies, it will be necessary to improve the specified model by introducing additional coefficients, for example, the communication coefficient, which will increase or decrease the dependence of the coefficients of external and internal influences, etc.

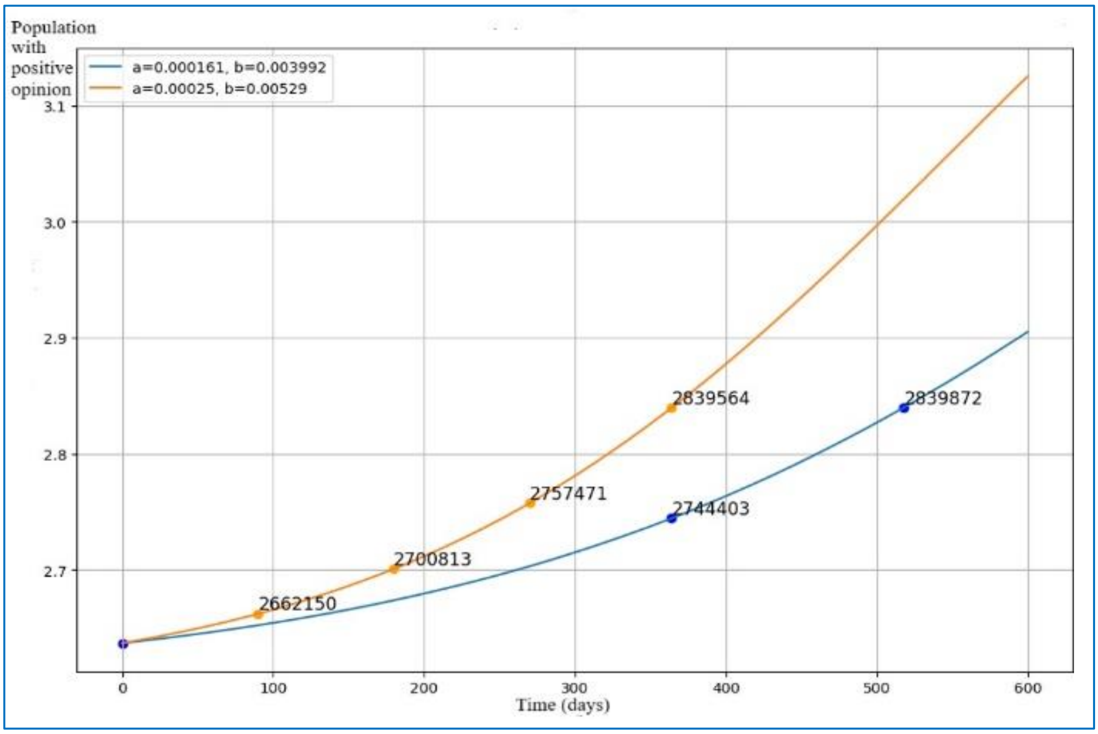

Fig. 7. Comparison of models according to the purpose of information activities during an information operation

Thus, taking into account the modeling and the results obtained, we can state that if the increase does not correspond to the specified data, there is a need to revise the content strategy. The content strategy in this study is proposed to be defined as a comprehensive plan that outlines the creation, distribution and management of content to achieve specific goals and objectives. It involves the development and implementation of an approach to content creation taking into account the defined target audience, the social network platform used, as well as the general goals of information activities during the information operation. Therefore, one of the main factors remains the definition and assessment of the target audience in the social network.

4. The application of neural networks for the study of information/disinformation dissemination. With the advent of artificial intelligence, the possibility of using it to spread information or disinformation has significantly increased.

Neural networks are a powerful and flexible tool for forecasting [19-21]. When determining what exactly should be predicted, it is necessary to specify the variables that are analyzed and used in the forecasting process. The level of detail plays an important role, which depends on various factors: the availability and accuracy of information, the cost of analysis and user expectations regarding the results obtained. If the optimal set of variables is not obvious, you can consider several options and choose the one that demonstrates the best result. This is usually the approach to creating forecasting systems based on the analysis of historical data.

The main disadvantages of using neural networks in forecasting include long training times, the risk of overtraining, difficulties in determining the optimal training sample, and working with a large number of input parameters.

The process of solving forecasting problems can be presented as a certain sequence of stages (Fig. 8).

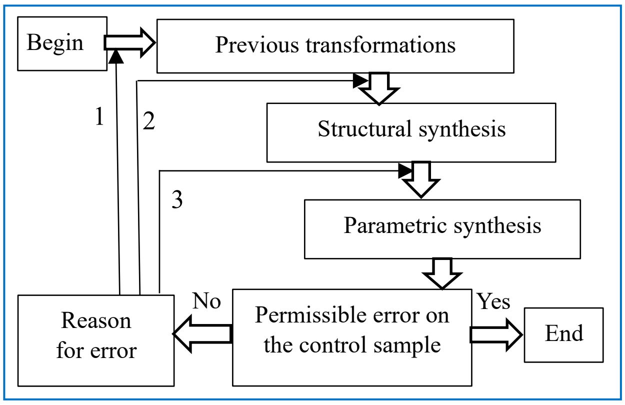

Fig. 8. The scheme for solving forecasting problems

The content of each of the stages of building a neural network for predicting information dissemination is given in Table 2. Depending on the forecasting task, different types of neural networks can be used.

Fully connected neural networks, known as Feedforward Neural Networks (FNN), belong to the early and fundamental architectures in the field of artificial intelligence. Despite their relatively simple structure, they demonstrate high efficiency in a wide range of tasks.

Main characteristics of FNN:

- *Structure:* A network consists of several layers of neurons, where each element of one layer has a connection to all neurons of the next layer. Typically, one or more hidden layers are located between the input and output layers.
- *Data transfer:* Information in an FNN propagates in only one direction – from input to output, with no cyclic connections or backpropagation.

Table 2 – **Content of the stages of building a neural network for forecasting**

Stage	Description
Previous transformations	The source information is processed to reduce the prediction error.
Neural network training	Restoring the objective function from a sample of training data, which is a solution to the interpolation problem.
Using the network	Applying the obtained dependence to calculate the predicted value, i.e. performing extrapolation.
Structural synthesis	Choosing an architectural model and forming connections between neurons.
Parametric synthesis	Learning using the backpropagation error algorithm, which allows estimating the error of hidden neurons.
Calculation of synaptic coefficients	Determining the weight parameters of neurons using sample samples, without using analytical methods.
Checking the forecast error	Error analysis on control data. If it is within acceptable limits, the model is considered suitable for forecasting.

- *Activation functions:* Neurons use activation functions, such as sigmoid, hyperbolic tangent, or ReLU (Rectified Linear Unit), to determine whether a neuron will be activated and what signal it will transmit next.

FNNs are used to solve a wide range of problems, from binary classification to regression analysis. They are effective in cases where the input and output data can be clearly defined, and there is no need to consider time dependencies or sequences.

Advantages and limitations

- *Advantages:* Simplicity of design, clarity of learning algorithms, flexibility in application to different types of information.
- *Limitations:* They are inefficient when processing data with temporal or spatial relationships, such as in image analysis or natural language processing. They can also suffer from overtraining when working with too complex tasks.

FNNs remain a key tool for researchers and engineers working in the field of artificial intelligence. Due to their versatility, they are a starting point for understanding more complex neural network architectures and the basis for many modern solutions in this field.

In predictive systems, fully connected neural networks play an important role, applying their analysis capabilities to predict events and identify trends.

Convolutional Neural Networks (CNN) and Graph Neural Networks (GNN) can be used to classify information or detect disinformation in socio-cyber-physical systems. For example, CNN can analyze text or content to detect false information. GNN works with graph structures, which allows you to study how rumors spread in the network and find nodes that are the main sources of disinformation.

Convolutional Neural Networks (CNNs or ConvNets) are one of the main deep learning architectures, especially effective for working with visual data. They have a specific structure that allows for automatic and efficient feature extraction from images.

- *Local perception and sharing of scales:* Unlike fully connected models, in CNN each neuron only works with a specific part of the input image (receptive field). This helps the network learn spatial feature hierarchies.
- *Convolutional operations:* The main component of a CNN is the convolutional layers, where filters (kernels) are applied to extract key features of the input data.
- *Pooling (subsampling):* This layer is usually located after the convolutional layer and performs dimensionality reduction while preserving important features.

Main applications

CNNs are widely used in many areas, including:

- *Image and video recognition:* It is the basis of modern identification and classification systems, ranging from objects in photos to streaming video analysis.
- *Medical diagnostics:* Used to analyze medical images (MRI, X-ray images) to detect pathologies.
- *Text data processing:* Although CNNs were originally developed for image analysis, they are also used in NLP to work with text at the character or word level.

Advantages and limitations

- *Advantages:*
  - High efficiency in image processing due to the ability to automatically analyze spatial structures.
  - Fewer parameters compared to fully connected networks, which reduces the complexity of training.
- *Limitations:*
  - High demand for computational resources, especially when training on large datasets.
  - Main specialization is visual information processing, although expansion into other areas is possible.

CNNs remain one of the most important and rapidly evolving technologies in the field of artificial intelligence and machine learning. They find applications in various forecasting tasks due to their ability to efficiently analyze visual data and detect complex patterns.

For the data on the dynamics of information dissemination (time, number of individuals in different states, network topology), neural networks, in particular *recurrent neural networks (RNN)* or *LSTM*, can be used to predict the future state of the system. Thus, the use of LSTM is possible to predict the number of "infected" (information spreaders) in the SIR model based on data from previous steps.

At the same time, training a neural network is possible on historical data to predict the speed of information dissemination depending on network parameters (for example, connections between nodes).

Recurrent neural networks (RNNs) are a class of models that are optimized for working with sequential data, such as time series, text, or audio. They can take previous values into account when processing current values, making them ideal for tasks where context plays an important role.

- *Feedback loops:* A distinctive feature of RNNs is the presence of feedback loops that allow data to circulate within the network. This allows information about previous inputs to be stored, influencing subsequent processing.
- *Working with sequences:* Networks of this type are capable of working with variable-length input data, which makes them suitable for text or speech analysis, where the number of elements in a sequence can vary significantly.

Main areas of application

RNNs are widely used in tasks where the context and order of data arrival matter:

- *Natural Language Processing (NLP):* Used for speech recognition, text analysis, and automatic text generation tasks.
- *Time series forecasting:* In financial analytics, meteorology, and other fields, they help predict future events based on previous values.
- *Audio and video analysis:* They are used for sound recognition, speech processing, and video stream analysis, for example, in object or event detection tasks.

Advantages and limitations

- *Advantages:*

o *Remembering context:* The ability to store information about previous elements of a sequence is critically important for many applications.

o *Flexibility in working with sequences:* The network is not tied to a fixed length of input data, which makes it versatile for various tasks.

- *Limitations:*

o *Problems with long-term sequences:* Traditional RNNs suffer from "gradient fading", which makes it difficult to train on long sequences.

o *High computational costs:* Due to the sequential nature of data processing, it is difficult to effectively parallelize processes, which increases training time.

RNNs remain a key tool in the field of sequential data processing, as they allow for the analysis of temporal dependencies and the construction of predictions based on them. They occupy a special place in the field of machine learning, providing efficient detection of patterns in data, which is critical for forecasting.

In addition, neural networks provide a solution to the optimization problem. Thus, using neural network approaches such as deep reinforcement learning (Reinforcement Learning), it is possible to determine which nodes to activate so that information spreads the fastest).

The use of Deep Q-Learning provides the selection of key nodes in the network that need to be activated to ensure maximum information dissemination.

Generative Adversarial Networks (GANs) can be used to create synthetic data that resembles real-world information dissemination scenarios. This is useful when real-world data is not available.

In addition, the integration of distribution models with neural networks provides a combination of classical models (SIR, Daley-Kendall) with neural networks to take into account more complex parameters:

train a neural network to predict model parameters (β and γ in SIR).

Add "noise" to the system to simulate realistic processes and use a neural network to adaptively adjust the models.

However, their use has significant disadvantages [18]:

– *Data volume*. Neural networks require a large amount of data to train, which can be a problem if you don't have historical data on rumor spreading.

– *Interpretation of results*. Neural networks sometimes work as a “black box.” Integration with classical models can help make the process more transparent.

– *Network size*. For large social networks, modeling can be computationally complex.

Forecasting the number of social network subscribers and modeling user reach in the context of such an important topic as Ukraine's accession to NATO can be implemented using various data analysis and machine learning methods.

For this, can be used the following technique:

Stage 1. Data collection and preparation

To implement the task, the following data is required:

– historical data on the number of page subscribers (time series);

– data on user activity (likes, comments, reposts);

– thematic trends regarding NATO in social networks (frequency of mentions, popularity of posts);

– data on the population of Ukraine (demographic, regional);

– information on the coverage of publications (reach, engagement indicators).

The following open sources may be used:

Social network APIs (e.g. Facebook Graph API or YouTube API).

Population surveys (e.g. sociological survey data).

Google Trends analytics on the topic of NATO.

Stage 2. Building a subscriber prediction model

To predict the number of subscribers, you can use recurrent neural networks (RNN) or autoregressive models (ARIMA). LSTM would be a good choice because this type of RNN works well with time series.

Stage 3. Coverage modeling

To model reach, the following are used:

– SIR-like models to estimate the information dissemination process;

– social graphs, where nodes represent users and edges represent their interactions;

– simulation modeling (Monte Carlo model) to estimate reach under different scenarios.

Stage 4. Using neural networks to assess commitment

Creating a model based on machine learning (e.g. Random Forest, Gradient Boosting) for classifying NATO-related sentiment. Input data:

– likes/reposts on NATO-related content;

– comment texts with sentiment analysis (Sentiment Analysis).

To model reach, it is proposed to use:

– SIR model – information dissemination model (e.g. from previously provided ones);

– graph analysis – libraries such as NetworkX for modeling interactions in social networks;

– Sentiment Analysis – assessment of attitudes towards NATO, libraries such as NLTK or Transformers.

To confirm the proposed method, a simulation was conducted based on building an LSTM model on the available data (Table 1). At the same time, the assessment of the quality of the forecast on the test data provides the following indicators:

– mean square error (mse): 120007542.91;

– root mean square error (rmse): 10954.80;

– mean absolute error (mae): 10757.41;

– mean absolute percentage error (mape): 1.31%.

Fig. 9 shows the results of forecasting data until June 2025.

The obtained predictive values are given in Table 3.

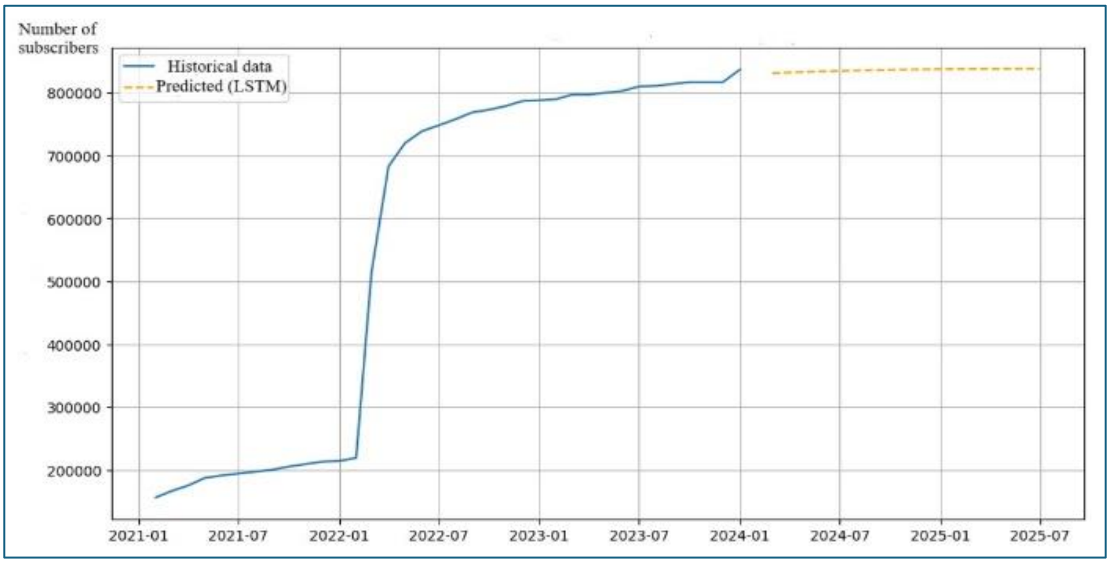

Fig. 9. Results of data forecasting until June 2025 based using an LSTM model

Table 3 – **Forecast data until June 2025**

Data	Number of subscribers	Data	Number of subscribers
2024-02-29	831215	2024-11-30	837265
2024-03-31	832269	2024-12-31	837556
2024-04-30	833217	2025-01-31	837814
2024-05-31	834091	2025-02-28	837907
2024-06-30	834859	2025-03-31	838035
2024-07-31	835525	2025-04-30	838142
2024-08-31	836066	2025-05-31	838231
2024-09-30	836539	2025-06-30	838305
2024-10-31	836936		

The obtained data can be considered reliable, which is emphasized by the high quality of the model according to the main evaluation indicators. According to the obtained results, it can be argued that in order to sharply increase the number of informed people about the advantages of Ukraine's accession to NATO and the corresponding increase in support for this process, it is necessary to develop a new information strategy. A successful strategy will make it possible to realize rapid audience growth. Such conclusions are fully correlated with the results of the innovation diffusion model and confirm the need for qualitative changes in the content strategy of the relevant social media.

Conclusions

The study of statistical data showed that the nature of information consumption has changed over time, in particular, the level of active monitoring of news has decreased, and users have started to focus on everyday matters again. At the same time, social media remain important channels of information, with a high level of trust in the news distributed through these platforms. This highlights the need to adjust the information influence strategy taking into account changes in the consumption habits of the audience.

Social media has become a major platform for implementing strategic narratives that directly influence public consciousness. Platforms that allow for real-time interaction (likes, comments, reposts) have been found to be effective in spreading information and shaping public opinion. This points to the importance of interactivity and adapting content to the platform and audience to achieve maximum impact.

Using Bass's model of diffusion of innovations, we investigated the dynamics of the dissemination of information products (narratives) among social media users.

According to the results, for the effective dissemination of narratives, it is important to correctly target innovators and imitators, creating appropriate content for different groups of consumers. The model showed that to optimize the dissemination process, it is necessary to take into account both media communication and personal communication in networks.

The use of LSTM architecture for forecasting changes in socio-political sentiments showed high accuracy of results, in particular in predicting the growth of support for certain narratives. The assessment of the quality of the forecast (MSE, RMSE, MAE) confirmed the high reliability of the obtained data, which emphasizes the effectiveness of using neural networks for analyzing social trends in real time.

Based on the results of the modeling it was determined that in order to achieve a significant increase in awareness in society, it is necessary to review the approaches to the creation and distribution of content. It is recommended to create content, focusing on the target audience and using more effective communication channels, such as messengers and specific social networks.

The assessment of the modeling results showed that adapting the content strategy can significantly improve outreach and interaction with the audience, which is critical for the successful implementation of the strategic narrative.

Therefore, the results of the study confirm that the use of predictive models and data analysis in combination with effective content strategies are necessary for the successful implementation of strategic communications in social media. Forecasting public sentiment and monitoring changes in consumer habits are important aspects for adjusting information policy and increasing its effectiveness in the face of constant changes in the digital environment.

Thus, taking into account the modeling and the results obtained, it can be argued that if the increase does not correspond to the specified data, it is necessary to revise the content strategy. Content strategy in this study is proposed to be defined as a comprehensive plan that outlines the creation, distribution and management of content to achieve specific goals and objectives. It involves the development and implementation of an approach to content creation taking into account the identified target audience, the social media platform used, as well as the overall goals of information activities during the information operation. Therefore, one of the main factors is the definition and assessment of the target audience in the social network.

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ВІДОМОСТІ ПРО АВТОРІВ/ ABOUT THE AUTHORS

Романюк Роман Васильович – начальник управління психологічної підтримки персоналу, Командування Сухопутних Військ Збройних Сил України, Київ, Україна;
Roman Romaniuk – Chief of Personnel Psychological Support Department, Ukrainian Land Forces Command, Kyiv, Ukraine;
e-mail: r.romaniuk@post.mil.gov.ua; ORCID Author ID: https://orcid.org/0009-0009-5439-1493.

Войтко Олександр Володимирович – кандидат військових наук, доцент, начальник інституту стратегічних комунікацій, Національний університет оборони України, Київ, Україна;
Oleksandr Voitko – Candidate of Military Sciences, Associate Professor, Head of the Institute of Strategic Communications, National Defence University of Ukraine, Kyiv, Ukraine;
e-mail: o.voytko@ukr.net; ORCID Author ID: https://orcid.org/0000-0002-4610-4476;
Scopus ID: https://www.scopus.com/authid/detail.uri?authorId=57210362201.

Пархуць Любомир Теодорович – доктор технічних наук, професор, професор кафедри захисту інформації, Національний університет "Львівська політехніка", Львів, Україна;
Liubomyr Parkhuts – Doctor of Technical Science, Professor, Professor of Information Protection Department, Lviv Polytechnic National University, Lviv, Ukraine;
e-mail: Liubomyr.T.Parkhuts@lpnu.ua; ORCID Author ID: https://orcid.org/0000-0003-4759-9383;
Scopus ID: https://www.scopus.com/authid/detail.uri?authorId=8218306100.

Рахімов Володимир Володимирович – доктор філософії, начальник кафедри соціальної комунікації та публічної дипломатії,, Національний університет оборони України, Київ, Україна;
Volodymyr Rakhimov – Doctor of Philosophy, Head of the Social Communication and Public Diplomacy Department, National Defence University of Ukraine, Kyiv, Ukraine;
e-mail: v.rakhimov@edu.nuou.org.ua; ORCID Author ID: https://orcid.org/0000-0001-9868-986X.

Костяк Марина Юріївна – кандидат технічних наук, доцент, доцент кафедри захисту інформації, Національний університет "Львівська політехніка", Львів, Україна;
Maryna Kostiak – Candidate of Technical Sciences, Associate Professor, Associate Professor of the Department of Information Protection, Lviv Polytechnic National University, Lviv, Ukraine;
e-mail: Maryna.Y.Kostiak@lpnu.ua; ORCID Author ID: https://orcid.org/0000-0002-6667-7693;
Scopus ID: https://www.scopus.com/authid/detail.uri?authorId=57686638700.

Моделі прогнозування змін громадської думки під час реалізація наративу в соціальних медіа

Р. В. Романюк, О. В. Войтко, Л. Т. Пархуць, В. В. Рахімов, М. Ю. Костяк

Анотація. Актуальність. У сучасному світі соціальні медіа стають основними каналами комунікації, що суттєво впливає на формування громадської думки та реалізацію стратегічних наративів. У контексті глобальних інформаційних викликів, зокрема війни, розуміння та прогнозування змін суспільних настроїв є надзвичайно важливим для ефективної реалізації державної інформаційної політики, а також для боротьби з дезінформацією. **Предметом дослідження** є моделювання процесів прогнозування змін громадської думки під час реалізації стратегічного наративу через соціальні медіа. **Метою дослідження** є аналіз ефективності застосування моделей дифузії інновацій та нейронних мереж для прогнозування змін у суспільно-політичних настроях, а також оптимізація контент-стратегії на платформах соціальних медіа. **Основні результати:** Дослідження показало, що соціальні медіа мають значний вплив на громадську свідомість, і використання моделей розповсюдження інформації, таких як модель дифузії інновацій Басса, дозволяє прогнозувати поширення наративів серед різних груп користувачів. Використання нейронних мереж для аналізу суспільно-політичних настроїв забезпечило високоточні прогнози з хорошими показниками якості. **Результати дослідження** підкреслюють важливість адаптації контент-стратегії в соціальних медіа для підвищення ефективності впливу на аудиторію. **Висновок.** Отримані результати підтверджують, що для успішної реалізації стратегічного наративу держави необхідно застосовувати комбіновані методи прогнозування та адаптації контенту на соціальних платформах. Успішна адаптація контент-стратегії, з урахуванням змін у поведінці користувачів та тенденцій у суспільно-політичних настроях, є ключовим фактором для ефективного впливу на громадську думку і підтримки національних інтересів у цифровому середовищі.

Ключові слова: громадська думка; соціальні медіа; стратегічні комунікації; дифузія інновацій; модель Басса; нейронні мережі; дезінформація; прогнозування; контент-стратегія.