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A MULTIFACTOR MODEL FOR DETECTING PROPAGANDA IN TEXTUAL DATA

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Detecting elements of propaganda in large volumes of textual data is currently one of the key tools in combating the information warfare taking place worldwide. This paper presents a multifactor model for determining the level of propaganda in a publication. The analyzed publications included text-based news articles and social media posts, which were processed using both quantitative and semantic text analysis methods. The model was constructed using the method of linear convolution, which enables the integration of multiple heterogeneous indicators into a unified value reflecting the degree of propaganda.

The proposed model considers thirteen indicators, each of which, when exhibiting a high value, signals the potential presence of propaganda within a text. The indicators encompass lexical, syntactic, and semantic characteristics such as emotional tone, subjective evaluation, presence of manipulative triggers, and calls to action. The value of each indicator was calculated using methods of statistical analysis, intelligent data analysis, and machine learning.

An algorithm for determining the influence level of each factor was proposed, as well as a scale for assessing the overall level of propaganda. For every analyzed publication, a utility function value was computed to quantify its propaganda intensity. The threshold value of this utility function – beyond which a publication is considered propagandistic – was defined as the sample mean across the dataset. This approach allows for an objective classification of textual materials without the need for expert labeling.

The advantage of the developed method lies in the fact that each indicator is derived exclusively from empirical statistical data and validated computational procedures, ensuring the elimination of human subjectivity. The study demonstrates that the modified multifactor model can serve as a universal analytical tool for detecting propaganda in various types of textual data, thereby enhancing the transparency and reliability of media content analysis.

Keywords: information technology, propaganda, publication, multifactor model, statistical analysis, data mining, machine learning, text mining, recommendations.

1. Introduction

Propaganda – is a form of communication aimed at influencing the opinions, attitudes, or actions of a large group of people. It is often used by governments, political parties, corporations, or other organizations to promote a particular ideology, policy, or product. Propaganda can be both positive and negative, but it is often associated with information manipulation and disinformation used to achieve specific goals.

The relevance of detecting propaganda in news content is extremely high in today's information environment. There are several reasons why this issue is of great importance:

1. Protection of democracy. Democratic societies rely on well-informed citizens capable of making conscious choices. Propaganda can distort reality and manipulate public opinion, thereby undermining democratic processes.

2. Spread of disinformation. Propaganda frequently relies on disinformation or distorted facts to achieve its objectives. This can result in the public receiving false information, which may in turn cause panic, unjustified fears, or hatred.

3. Political manipulation. Governments or political groups may use propaganda to influence public opinion in favor of their political agendas, potentially leading to unfair elections or other political advantages.

4. Social consequences. Propaganda can deepen divisions within society, spread hatred and discrimination, and increase levels of violence. This may lead to social instability and conflict.

5. Economic consequences. Disinformation can affect financial markets, cause economic disruptions, and undermine trust in businesses and economic institutions.

6. Public health. During pandemics or other crises, propaganda and disinformation can have serious consequences for public health by fostering mistrust in medical advice, vaccinations, and other health protection measures.

7. International Relations. Propaganda can influence international relations, create tensions between countries, and contribute to conflicts. This may have far-reaching consequences for global security and stability.

At present, the following methods are used to detect propaganda:

1. Content analysis – employing algorithms to analyze text and identify propagandistic techniques such as emotionally charged language, exaggeration, or the use of stereotypes.
2. Fact-checking – establishing fact-checking platforms that can analyze information and indicate whether it is accurate or false.
3. Educational programs – enhancing media literacy among citizens so that they can independently recognize propaganda and disinformation.
4. Collaboration with technology companies – developing tools and algorithms for social media platforms that can detect and label propaganda and disinformation.
5. Network dissemination analysis – studying how propagandistic materials spread online, including the identification of key actors and distribution channels.

Detecting and countering propaganda in news media are crucial components in maintaining a healthy information environment that promotes informed decision-making by citizens and supports democratic values.

Having established the relevance of the problem of propaganda detection and the main methods of its study, it is essential to examine how this issue is addressed in scientific literature. An analysis of existing research makes it possible to identify methodological approaches, problematic aspects, and future directions for the development of propaganda detection systems.

2. Literature review and problem statement

Understanding propaganda through scientific analysis requires an interdisciplinary approach that integrates history, psychology, sociology, political science, and technology. By studying existing literature and case studies, researchers can form a comprehensive understanding of how propaganda operates and its far-reaching consequences.

An analysis of scholarly articles on propaganda reveals a diversity of approaches and conclusions in this field. Researchers increasingly apply advanced methods for detecting and analyzing propaganda in news content, including the use of machine learning models such as `BERT` and `GPT-4`. These models are trained to detect and classify various propaganda techniques in textual data.

In [1], the authors presented the results of a study employing a pre-trained `BERT` to improve the detection of propagandistic material in news articles. This model processes text at the word level and integrates features at the sentence level, enabling it to effectively distinguish between propagandistic and non-propagandistic content. The study highlighted challenges such as data imbalance and proposed methods like oversampling and data augmentation to address them.

In [2], the researchers presented a study focused on the annotation and detection of propagandistic materials using `GPT-4`. The research involved a multi-stage annotation process to ensure high data quality. The resulting dataset included annotated paragraphs from various news sources, allowing for an in-depth analysis of propaganda techniques across different topics and domains.

The publication [3] presented an analysis of the impact of propaganda on the political landscape in the United States. It was found that the spread of disinformation in the media had a profound effect on social discourse and politics in the U.S. Consequently, detecting such content has received significant attention and yielded notable results; however, the detection process remains complex. The study proposed the development of an ontology specifically aimed at propaganda detection, drawing upon multiple disciplines including computer science and the social sciences.

In [4], the authors conducted a detailed text analysis by identifying all fragments containing propaganda techniques and categorizing their types. Specifically, a corpus of news articles was manually annotated at the fragment level using eighteen propaganda techniques, and an appropriate evaluation metric was proposed. Additionally, a new neural network based on `BERT` was developed.

In publication [5], a methodology for assessing the credibility of questionable information is presented, based on calculating the shortest path between conceptual nodes according to well-defined semantic proximity metrics within knowledge graphs.

Study [6] provides a systematic overview of the origins and evolution of information warfare methodologies and highlights the differences among the American, British, and Russian models. The concept of the *"war of meanings"* is introduced for the first time, with an analysis of its role in the modern world.

It is important to emphasize that the aforementioned machine learning models rely on the principle of supervised learning, meaning they require human involvement in the creation of initial training datasets. This introduces an element of subjectivity into the decision-making process regarding whether a particular article exhibits propagandistic features.

It should also be noted that, at present, social media platforms play a major role in the dissemination of propaganda, serving as the primary means of information exchange and communication among people [7].

In particular, article [8] proposes a new model called `CatRevenge`, which identifies aspects of unhealthy communication in social media, including both active and passive forms of revenge – phenomena that are also related to the concept of propaganda. This model is preprocessed using an internet slang meaning dictionary to more effectively detect revenge-related text. `Slangzy` assigns an influence weight to each part of speech in a sentence based on its relevance and the sentiment score of the words. The proposed model `CatRevenge` also incorporates a paragraph embedding framework for contextual semantic analysis of revenge-related text. Furthermore, the study applies a gradient-boosted categorical feature classifier `CATBoost` to reduce model overfitting and improve overall performance.

As a result of the research presented in study [9], individuals who influence knowledge exchange processes through an internal social network were identified, and future knowledge flows were predicted. In other words, the study examines the ideological impact of propaganda. Consequently, a four-phase methodology was proposed, combining social network analysis with structural modeling techniques.

Study [10] investigated the influence of social media posts by well-known individuals on cryptocurrency exchange rates. The research was conducted using statistical analysis, and the findings revealed that posts by influential figures on social media have a significant impact on cryptocurrency values. Thus, this study serves as an example of propaganda within the commercial domain.

Article [11] focuses on the problem of detecting propaganda in text files. It discusses various methods for solving text classification tasks related to spam filtering, contextual advertising, news categorization, and the creation of thematic directories.

Study [12] presents a multifactor model for determining the level of propaganda in a publication. The analyzed materials included text-based news articles and social media posts. The model was developed using the linear convolution method. Within this framework, ten indicators were considered, each of which – when exhibiting a high value – indicates the potential presence of propaganda in the publication. The proposed model is based exclusively on statistical data and computations performed using data mining algorithms, statistical analysis, and decision theory.

Article [13] provides an overview of multilingual models designed to work with limited datasets and analyzes their development. The following models are examined: `XLM-RoBERTa`, `mBERT`, `LASER`, `MUSE`.

These studies highlight the importance of employing advanced machine learning techniques, statistical analysis, data mining, and meticulous data annotation processes for the detection and analysis of propaganda. They provide valuable insights into the methodologies that can enhance the accuracy and reliability of propaganda detection systems – an essential factor for understanding and mitigating the influence of propaganda.

It should be noted that the process of propaganda detection still requires the development of diverse mathematical models to achieve more precise and comprehensive identification of this form of communication.

Furthermore, it is worth emphasizing that none of the existing models have been applied to the identification of propaganda within the musical and theatrical arts in general, or within opera art in particular.

Study [14] proposes a modified version of the Multifactor model for detecting propaganda (MMDP), originally introduced in [12], for assessing the level of propaganda in the librettos of world operas. In addition, the study examined the degree of correlation between the propaganda detection results obtained using the MMDP and the opinions of experts in opera art.

It should be emphasized that the process of detecting propaganda in texts of various domains requires further improvement in model accuracy. This issue is the focus of the present study. For conducting experimental research with the modified model (MMMDP – Modified multifactor model for detecting propaganda), an information technology framework was developed that integrates machine learning, statistical analysis, and data mining.

Based on the literature review and the identified challenges in propaganda analysis, specific objectives and research tasks are formulated. These tasks determine the direction of developing the modified multifactor model for propaganda detection and substantiate its scientific novelty.

3. Research aim and objectives

The aim of the study is to improve the multifactorial model for detecting propaganda (MMMDP) by creating a modified multifactorial model for determining propaganda (MMDP). This model allows for a more accurate assessment of the level of propaganda influence in news publications and social networks based on the integration of new indicators and changes in the approach to calculating existing ones.

En accordance with the purpose of the study, the following objective was set: develop an MMMDP based on the MMDP with the introduction of new features (factors) of the presence of propaganda and modification of the algorithms for calculating their numerical metrics, weights, and overall value function

Defining the goal and formulating the research task allow us to move on to the development of a practical methodology. The next section describes in detail the materials and methods used to build and test the modified multifactor model for detecting propaganda.

4. Materials and methods of the study

4.1. General concept of the MMMDP

The detection and assessment of the level of propagandistic influence is a task that requires a systematic approach. To address this, a multifactor model is proposed, based on the linear convolution method (see Fig. 1). This method allows for the integration of multiple heterogeneous indicators into a single composite index, reflecting the overall level of propagandistic influence.

Research object: the process of detecting and quantitatively assessing propaganda in news publications, social media posts, and opera librettos, in particular the use of statistical and semantic characteristics of texts to determine the level of manipulative influence.

Fig. 1. Main stages of the MMMDP

Subject of the study: MMMDP, as well as methods for calculating value function metrics to determine the level of propaganda based on the analysis of 13 text features, including emotional coloring, trigger words, clickbait headlines, repetitive theses, subjectivity, calls to action, and others. The following subsection considers the advantages and disadvantages of the proposed model.

After presenting the general concept of a multifactorial model for assessing propaganda influence, as well as the object and subject of the study, a question arises. It concerns which characteristics should be used to evaluate texts. The following subsection justifies the selection of characteristics that capture both the formal and semantic-rhetorical properties of publications.

4.2. Justification for the selection of features

The proposed model considers the following features of propaganda:

$$x_1 = \{\text{emotional tone of the text}\}\,;$$
$$x_2 = \{\text{provocative terms}\}\,;$$
$$x_3 = \{\text{lexical and syntactic simplicity of the text}\}\,;$$
$$x_4 = \{\text{unreliability of the source}\}\,;$$
$$x_5 = \{\text{socially sensitive narratives}\}\,;$$
$$x_6 = \{\text{emotionally provocative patterns}\}\,;$$
$$x_7 = \{\text{subjectivity of judgments}\}\,;$$
$$x_8 = \{\text{mobilization rhetoric}\}\,;$$
$$x_9 = \{\text{rhetorical duplication}\}\,;$$
$$x_{10} = \{\text{coordinated publication activity}\}\,;$$
$$x_{11} = \{\text{signs of messianism}\}\,;$$
$$x_{12} = \{\text{opposing oneself to enemies}\}\,;$$
$$x_{13} = \{\text{opposing oneself to “invisible enemies”}\}\,.$$

The set of these features is denoted by $X = (x_1, \ldots, x_{13})$.

The selection of these characteristics is justified by the fact that they reflect both the formal properties of texts (such as word count, repetitions, and shares) and rhetorical or semantic elements (such as emotionality, clickability, and benefit to stakeholders) [12, 14]. Combining these levels helps avoid reductionism and provides a foundation for a comprehensive analysis. A more detailed justification for the selection of each criterion is provided in Section 4.3.

Considering the chosen features, it becomes possible to construct a multifactor model in practice. The following subsection outlines the step-by-step process for calculating metrics, determining factor importance, and computing the integral value function for each publication.

4.3. Stages of model construction

Let us consider a set of publications $P = (P_1, \ldots, P_l)$. The process of constructing a multifactor model consists of several logical stages (see Fig. 1).

STAGE 1. Calculation of propaganda level for each factor.

The input is a set of factors $X = (x_1, \ldots, x_{13})$. It is necessary to calculate numerical metrics that determine the level of propaganda for each of the specified factors [12, 14–17].

The output consists of metrics K_i^j, $i = 1, \ldots, 13$; $j = 1, \ldots, l$.

x_1. Emotional tone of the text (sentiment analysis).

Theoretical explanation. Propagandistic texts often appeal to emotional responses such as fear, anger, a sense of injustice, or national pride. Analyzing the emotional tone helps to identify the dominance of negative or mobilizing tones, which may indicate potential manipulativeness.

Practical implementation. In this study, sentiment analysis was conducted using deep learning-based models, specifically transformer-type (`RoBERTa`) architectures pre-trained on datasets labeled by emotional tone (model: `cardiffnlp/twitter-roberta-base-sentiment`). The analysis involved classifying texts into positive, negative, or neutral sentiment categories using a lexicon-based approach.

The numerical metric representing the emotional tone of a publication P_j is denoted as K_1^j. Evidently, $0 \leq K_1^j \leq 1$, and the closer its value is to 1, the more emotionally charged the publication is.

x_2. Provocative terms (trigger words).

Theoretical explanation. Propaganda often employs lexemes with a high emotional charge or markers of hostility, creating the image of an "enemy" or "betrayal." Identifying such words helps detect manipulative semantic centers.

Practical implementation. In this study, lexical analysis was conducted using dictionaries of trigger words, developed for specific cultural or political contexts. Methods of automatic phrase recognition (`PhraseMatcher` from the `spaCy` library) were used to identify key terms.

The metric for trigger words in a publication P_j is denoted as K_2^j. Clearly, $0 \leq K_2^j \leq 1$, and the closer its value is to 1, the greater the number of such words in the publication.

x_3. Lexical and syntactic simplicity of the text.

Theoretical explanation. Propagandistic messages are typically formulated in simple, accessible language, often using short sentences, simplified grammar, and a limited vocabulary. This facilitates rapid comprehension and enhances emotional impact.

Practical implementation. To assess the readability of a publication P_j, the Flesch Reading Ease Index [14, 18] was used, denoted as K_3^j and calculated using (1):

$$K_3^j = \left(206,835 - 1,015\frac{a_j}{b_j} - 84,6\frac{c_j}{a_j}\right)0,01, \tag{1}$$

where a_j is the total number of words, b_j is the total number of sentences, and c_j is the total number of syllables. These indicators were calculated using linguistic analysis tools (`textstat`).

The interpretation of this metric's values is shown in Table 1 [14].

Table 1. Interpretation of Flesch Reading Ease Index values

Score	School level	Notes
1,0-0,9	Grade 5	Very easy to read. Easily understood by an average 11-year-old student
0,9-0,8	Grade 6	Easy to read. Conversational language for consumers
0,8-0,7	Grade 7	Fairly easy to read
0,7-0,6	Grades 8-9	Standard language. Easily understood by 13-15-year-old students
0,6-0,5	Grades 10-12	Fairly difficult to read
0,5-0,3	College	Difficult to read
0,3-0,1	Technical Graduate	Very difficult to read. Best understood by university graduates
0,1-0,0	Professional	Extremely difficult to read. Best understood by university graduates

Clearly, $0 \leq K_3^j \leq 1$, and the closer its value is to 1, the easier the publication is to read.

x_4. Unreliability of the source (reputational assessment).

Theoretical explanation. Evaluating the reputation of a source is an important aspect of determining the credibility of a message. Propagandistic texts are often disseminated through sources with questionable reputations.

Practical implementation. In the process of calculating this indicator K_4^j for publication P_j, other similar publications in questionable sources were automatically pulled up within the current source. Thus, the average relative frequency of reposts was considered an index of distrust in the source. Clearly, $0 \le K_4^j \le 1$, and the closer its value is to 1, the less reliable the source is.

x_5. Socially sensitive narratives (trigger topics).

Theoretical explanation. Propaganda often exploits socially polarizing topics – such as nationalism, religion, security, migration, gender, war, and others. Identifying these thematic fields allows for the detection of potentially manipulative contexts.

Practical implementation. To determine the thematic structure of a text, `zero-shot` classification was used based on the `BART-large-MNLI` to verify the text's affiliation with predefined sensitive topics. The metric for trigger topics in a publication P_j is denoted as K_5^j. Clearly, $0 \le K_5^j \le 1$, and the closer its value is to 1, the greater the number of such topics in the publication.

x_6. Emotionally provocative patterns (clickbait headline).

Theoretical explanation. Clickbait headlines are used to artificially attract attention, often through exaggeration or emotional emphasis that does not reflect the content of the main text. Such discrepancies between the headline and the article may indicate a manipulative nature of the message or an attempt to influence the audience through cognitive dissonance.

Practical implementation. To detect clickbait, a semantic comparison between the headline and the main text was performed using a contextual embedding model (`Sentence-BERT`). The similarity coefficient (*cosinesimilarity*) is calculated (see (2)) between the headline vector and the content vector. A low level of semantic correspondence indicates potential clickbait. Additionally, lexical markers of sensationalism were analyzed, but the primary criterion is the mismatch between the expectation created by the headline and the actual content of the message.

The metric for the presence of clickbait in a publication P_j is denoted as K_6^j and calculated using (2):

$$K_6^j = cosinesimilarity\,(A_j, B_j) = \frac{\parallel A_j \parallel \cdot \parallel B_j \parallel}{(A_j \cdot B_j)}, \tag{2}$$

where the dot product of the headline word vectors A_j and content B_j, $\parallel A_j \parallel$ – the length (norm) of the vector A_j, $\parallel B_j \parallel$ – length of the vector B_j.

Clearly, $0 \le K_6^j \le 1$, and the closer its value is to 1, the more features of clickbait the publication exhibits.

x_7. Subjectivity of judgments (ratio of facts to opinions).

Theoretical explanation. The level of subjectivity in a text indicates the extent to which evaluative judgments, emotional statements, or assumptions prevail over objectively verifiable facts. High subjectivity often suggests an attempt to influence the reader's perception, which is a characteristic feature of propagandistic messages.

Practical implementation. To determine subjectivity, the [specify library] was used, which employs linguistic patterns and statistical approaches to classify sentences as objective or subjective. The model analyzes each sentence and returns a subjectivity coefficient ranging from 0 (completely objective) to 1 (completely subjective). The average value across the entire text is then calculated, allowing a quantitative assessment of the proportion of subjective statements and the potential manipulative nature of the material.

The subjectivity metric of a publication P_j is denoted as K_7^j. Clearly, $0 \le K_7^j \le 1$, and the closer its value is to 1, the more subjective the publication is.

x_8. Mobilizing rhetoric (call to action).

Theoretical explanation. Propagandistic texts often include direct or indirect calls to action – such as urging readers to support a particular position, join a movement, or protest. The presence of such elements indicates an attempt to influence audience behavior and mobilize emotional responses.

Practical implementation. To detect calls to action, vector analysis was applied to key marker words (e.g., "support," "act," "stop," "join"). In the proposed approach, the text is transformed into a vector representation, and the presence of marker words in the publication P_j and their proportion relative to the total number of sentences is calculated, denoted as K_8^j. Low-level semantic verification allows assessment of potential prompting structures without complex syntactic parsing.

Clearly, $0 \leq K_8^j \leq 1$, and the closer its value is to 1, the more calls to action the publication contains.

x_9. Rhetorical duplication (repeated claims).

Theoretical explanation. A hallmark of propaganda is the frequent repetition of key slogans and claims to reinforce a particular narrative.

Practical implementation. In the proposed approach, frequency analysis of n-grams and semantic grouping of similar expressions using vector representations (*cosinesimilarity*) are performed by (2). The repetition index K_9^j in a publication P_j is calculated as the average frequency of identical or similar phrases throughout the text.

Clearly, $0 \leq K_9^j \leq 1$, and the closer its value is to 1, the greater the repetition of a particular idea in the publication.

x_{10}. Coordinated publication activity (repeated texts in the source).

Theoretical explanation. Frequent repetition of identical or semantically similar materials within a single source or across multiple sources may indicate a targeted information campaign and an attempt to reinforce a particular narrative among the audience.

Practical implementation. In this approach, each document is represented as a vector embedding (using the `Sentence-BERT`), after which the similarity coefficient *cosinesimilarity* is calculated by (2) between all publications within the source.

Clearly, $0 \leq K_{10}^j \leq 1$, and the closer its value is to 1, the higher the repetition or duplication of messages, which may indicate coordinated propagandistic activity.

x_{11}. Signs of messianism.

Theoretical explanation. Messianic statements attribute to a single leader an exceptional ability to change societal circumstances or save the nation from threats. This rhetoric personalizes the political process and creates the effect of a "single possible path."

Practical implementation. In this study, semantic analysis was used to identify messianic rhetoric in texts. Detecting such rhetoric requires tools for intelligent text analysis, semantic processing methods, and natural language processing algorithms (NLP).

The messianic metric in this study is defined by (3):

$$K_{11}^j = \frac{d_j}{n_j}, \tag{3}$$

where d_j – is the number of messianic statements in the publication P_j, and n_j – is the total number of words in the publication P_j.

Clearly, $0 \leq K_{11}^j \leq 1$. An increase in this metric indicates a stronger emphasis on the role of a specific subject, which serves as an indicator of propagandistic influence.

x_{12}. Opposing oneself to enemies (generalization of opponents).

Theoretical explanation. Generalized statements about opponents create a simplified collective image of the enemy, stripped of individual distinctions. Such statements often use generalizing pronouns ("all," "they") combined with negative vocabulary.

Practical implementation. In this study, semantic analysis was employed to identify generalizing rhetoric (generalizing pronouns) in the text. Detecting this requires tools for intelligent text analysis, semantic processing methods, and natural language processing algorithms (NLP).

The generalization metric is defined by (4):

$$K_{12}^{j} = \frac{t_j}{n_j}, \tag{4}$$

where t_j – is the number of generalizing pronouns in the publication P_j; n_j – total number of words in the publication P_j.

Clearly, $0 \leq K_{12}^{j} \leq 1$. The higher this metric, the more the text encourages the audience to adopt a binary perception of reality ("us vs. them").

x_{13}. Opposing oneself to "invisible enemies".

Theoretical explanation. This technique is based on claims about the existence of "secret forces" or "invisible opponents" allegedly acting against society. Such messages appeal to fear and distrust while remaining unverifiable.

Practical implementation. To identify signs of contrasting oneself with "invisible enemies," tools for intelligent text analysis, semantic processing methods, and natural language processing (NLP) algorithms are applied. The contrast metric is defined by (5):

$$K_{13}^{j} = \frac{k_j}{s_j}, \tag{5}$$

where k_j – the number of mentions of "invisible forces" in the publication P_j; s_j – the total number of threatening statements in the publication P_j.

Clearly, $0 \leq K_{13}^{j} \leq 1$. An increase in this metric indicates active use of propagandistic techniques.

STAGE 2. Calculation of importance coefficients for each factor.

Input: metrics $K_i^j, i = 1, \ldots, 13; j = 1, \ldots, l$, calculated in STAGE 1.

It is necessary to calculate the importance coefficients for each criterion to compute the value function.

Output: coefficients ω_i.

To calculate the coefficients ω_i the following steps should be completed [14]:

STEP 1. From the metrics K_i^j form statistical samples with the corresponding name K_i^j.

STEP 2. Select a threshold value, above which a text can be considered propagandistic.

In this study, by analogy with the Chaddock scale [15, 16], which determines the strength of the correlation between two random variables, a scaling system was proposed, as presented in Table 2, as presented in [14].

Table 2. Level of propaganda in texts

Metric value for indicator K_i^j	**Characteristic of propaganda level**
0,0-0,1	No propaganda
0,1-0,3	Insignificant level of propaganda
0,3-0,5	Noticeable level of propaganda
0,5-0,7	Moderate level of propaganda
0,7-0,9	High level of propaganda
0,9-1,0	Very high level of propaganda

In this study, all levels of propaganda starting from the noticeable level were considered. Thus, the threshold value is set as $\overline{K_i} = 0,3$.

This threshold was introduced to facilitate subsequent statistical calculations and ease comparison of the obtained results.

It should be noted that, in general, scientific sources do not define a strict percentage threshold above which a text is considered propagandistic [19]. This study emphasizes the importance of qualitative analysis and the recognition of specific influence techniques, rather than establishing a universal quantitative threshold. Therefore, a more personalized approach for each propaganda feature is planned for future use.

STEP 3. If $K_i^j \geq \overline{K_i}$, the publication P_j is considered propagandistic with respect to indicator x_i. Otherwise, it is considered non-propagandistic. The publication is assigned a value 1, if it is propagandistic and a value 0 – otherwise (6).

$$P_j \to \widetilde{K_i^j} = \begin{cases} 1, & if\, K_i^j \geq \overline{K_i}; \\ 0, & if\, K_i^j < \overline{K_i}. \end{cases} \tag{6}$$

The conversion from quantitative values K_i^j to Boolean functions $\widetilde{K_i^j}$ was made for the convenience of subsequently calculating the frequency of propaganda detection for each feature $x_i, i = 1, \ldots, 13$.

STEP 4. Calculate the relative frequency of propagandistic publications for each feature x_i by (7).

$$w_i = \frac{m_i}{h}, \tag{7}$$

where m_i – number of propagandistic publications according to feature x_i; h – total number of publications in the dataset.

STEP 5. Normalize the relative frequencies w_i by (8):

$$\omega_i = \frac{w_i}{w_1 + w_2 + \ldots + w_{13}}. \tag{8}$$

STAGE 3. Calculation of the value function for publications.

Input: set of publications $P = (P_1, \ldots, P_l)$, metrics $K_i^j, i = 1, \ldots, 13; j = 1, \ldots, l$ and coefficients ω_i, calculated in STAGE 2.

For each publication, it is necessary to calculate the value function reflecting the presence of propaganda features.

Output: value function V_j for each publication.

The value function V_j, according to the linear convolution method [20, 21], is calculated using (9):

$$V_j = \sum_{i=1}^{13} \left(\omega_i \cdot K_i^j \right). \tag{9}$$

The calculation results can be presented in Table 3 [12, 14].

Table 3. Sample calculation table

	K_1^j	K_2^j	K_3^j	K_4^j	K_5^j	K_6^j	K_7^j	K_8^j	K_9^j	K_{10}^j	K_{11}^j	K_{12}^j	K_{13}^j	V_j
P_1	K_1^1	K_2^1	K_3^1	K_4^1	K_5^1	K_6^1	K_7^1	K_8^1	K_9^1	K_{10}^1	K_{11}^1	K_{12}^1	K_{13}^1	V_1
P_2	K_1^2	K_2^2	K_3^2	K_4^2	K_5^2	K_6^2	K_7^2	K_8^2	K_9^2	K_{10}^2	K_{11}^2	K_{12}^2	K_{13}^2	V_2
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
P_l	K_1^l	K_2^l	K_3^l	K_4^l	K_5^l	K_6^l	K_7^l	K_8^l	K_9^l	K_{10}^l	K_{11}^l	K_{12}^l	K_{13}^l	V_l

The resulting coefficients represent calculated weights that quantitatively reflect the significance of each propaganda feature in the overall ensemble. These weights are key elements for conducting ablation studies, as they allow us to evaluate the individual contribution of each factor to the final value function (9). The process of calculating importance coefficients, which is part of model calibration, is performed using the set of publications under study. Thus, ablation research conducted on this controlled sample allows us to most accurately identify the critical factors that most contribute to or hinder the correct detection of propaganda, thereby providing a reliable scientific justification for the inclusion of each individual factor in the final model. Thus, they act as automatic indicators of the importance of factors, allowing their inclusion in the model to be scientifically justified without taking human influence into account.

STAGE 4. Decision on whether a publication is propagandistic.

A set of publications $P = (P_1, \ldots, P_l)$ and a sample $V = \left(V_1, V_2, \ldots, V_l\right)$ obtained in STAGE 3 are submitted as input.

At the output, conclusions are formed about which of the publications $P = (P_1, \ldots, P_l)$ are propaganda.

Recommendations are formed according to the following rule [14]:

– if $V_j \geq \bar{V}$, $(j = 1, \ldots, l)$, then publication P_j is recommended as propaganda;

– if $V_j < \bar{V}$, $(j = 1, \ldots, l)$, then publication P_j is not recommended as propaganda.

In this rule, $\bar{V} = 0,3$ – the threshold value for sample V (by analogy with STEP 2 of STAGE 2) is determined by (10):

$$P_j \longrightarrow \widetilde{V_j} = \begin{cases} 1, & if\, V_j \geq \bar{V}, \\ 0, & if\, V_j < \bar{V}. \end{cases} \tag{10}$$

That is, the publication is assigned a value of 1 if it is propaganda and a value of 0 otherwise.

The correctness of the conclusions is evaluated using the $Recall$, $Precision$ and $F1-Score$ metrics, which are determined by formulas (11)-(13), respectively:

$$Precision = \frac{tp}{tp + fp}. \tag{11}$$

$$Recall = \frac{tp}{tp + fn}. \tag{12}$$

$$F1 - Score = \frac{2 \cdot Precision \cdot Recall}{Precision + Recall}. \tag{13}$$

It should be noted that binary representation was used for the convenience of calculating metrics (11)-(13) and when comparing different models. In addition, such representation of results is planned to be used in the future when training a neural network based on this model. Within the framework of this study, in addition to the Boolean representation, each publication was assigned a level of propaganda according to this scale (Table 1) $P_j \longrightarrow V_j$. This allows for a more detailed analysis of the level of propaganda in the publication. However, the ambiguity of such scaling should be taken into account.

Thus, the proposed model is multidimensional, multicomponent, and combines methods of classical statistics, deep learning, linguistic analysis, and semantic modeling. Its complexity manifests itself on several levels: structural, computational, conceptual, and interpretative. The overall complexity assessment is as follows (14):

$$T = \sum_{i=1}^{13} T_i \approx O\left(13 \cdot N + n \cdot d + s^2\right), \tag{14}$$

where n is the length of the text (tokens/words), d is the dimensionality of the model/vector, s is the number of sentences and N is the total number of records in the database.

Overall, after describing the methodology, selecting features, and calculating value functions based on the multifactor model, it is appropriate to proceed to the presentation of the obtained results. The next section summarizes the experimental testing data of the MMDP and MMMDP models, demonstrating the effectiveness of the modified approach.

5. Research results

5.1. Presentation of results obtained

This study combines two levels of data:

– statistical level – formal quantitative characteristics of texts (number of words, sentences, reposts, etc.);

– semantic level – rhetorical, emotional, and ideological features that cannot be easily quantified.

Based on this combined dataset, an integral metric is calculated, which makes it possible to determine whether a publication meets the criteria for propaganda.

However, it should be noted that, in general, there is no clearly defined percentage threshold in scientific sources above which a text is considered propaganda. That is why, in [15], the authors of this study proposed an appropriate scale (Table 2).

During testing of the MMDP and MMMDP models, the initial dataset consisted of approximately 100 publications.

In order to more clearly demonstrate the quality of the proposed model, a set of 10 publications that could be clearly classified as propaganda or not was selected for verification. In addition, it should be noted that the selected publications were written in their original language. The main results obtained on the basis of this sample of 10 publications are summarized in Table 4.

Table 4. Experimental results

#	Publication title	$\widetilde{V}_j$	V_j for MMDP	V_j for MMMDP	Improvement in %
P_1	Address by Emmanuel Macron on Europe's strategic vision	1	0,41	0,44	7,32
P_2	Speech by Marine Le Pen, presidential campaign 2017–2022	1	0,71	0,76	9,38
P_3	Trump's speech at the 2020 Tulsa rally	1	0,63	0,69	9,52
P_4	Trump's speech at the 2020 rally before the completion of the vote count	1	0,78	0,89	14,10
P_5	Hitler's address to the nation (September 1, 1939)	1	0,61	0,68	11,48
P_6	Hitler's speech at the sportpalast	1	0,68	0,77	13,24
P_7	Introduction to linear geometry	0	0,24	0,17	29,17
P_8	The magic of mathematics	0	0,20	0,19	5,00
P_9	Ocean exploration	0	0,23	0,17	26,09
P_{10}	Apple cultivation	0	0,25	0,18	28,00
Average value					15,33

Since the dataset contains publications for which it is obvious whether they are publications or not, it is easy to determine that $Precision = 1$; $Recall = 1$; $F1 - Score = 1$.

The visualization comparing the value function results for the specified models is presented in Fig. 2.

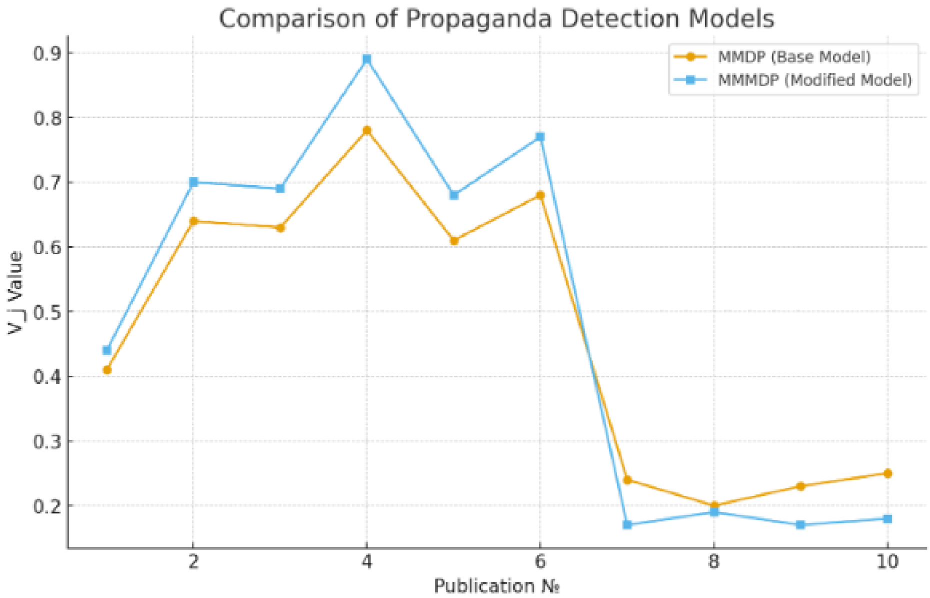

Fig. 2. Comparison of the results of MMMDP and MMDP

The comparison of improvements for the MMMDP model is presented in Fig. 3.

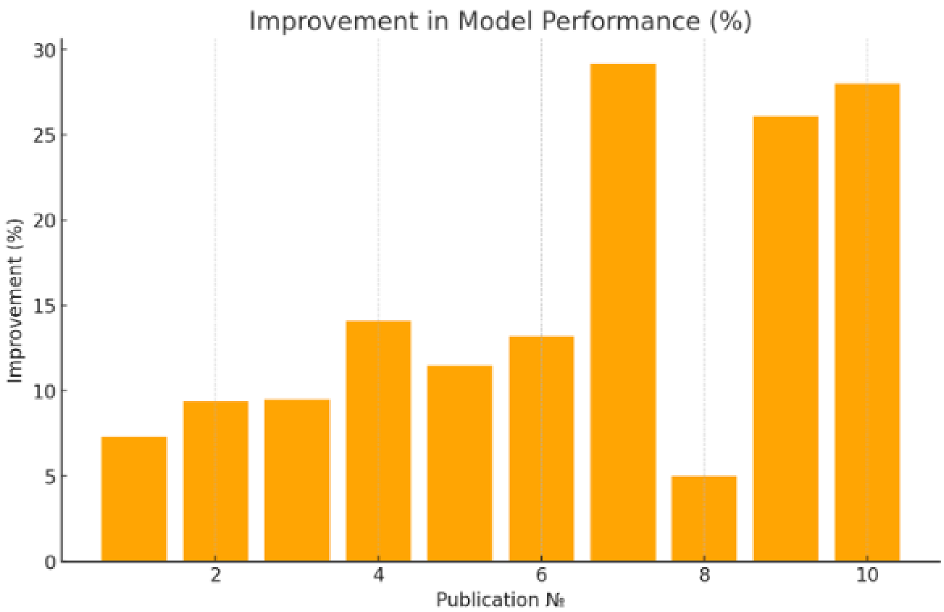

Fig. 3. Comparison of the improvement of MMMDP compared to MMDP

Table 5 also shows the values of the calculated weights ω_i in the MMMDP for the validation dataset. The distribution of weighting coefficients is shown in Fig. 4.

A comparison of text evaluation using the presented model and the `ChatGPT-4` system was also conducted. The main results are summarized in Table 6.

The results of comparing the speed of propaganda detection depending on text size are shown in Table 7.

Table 5. Calculated weights ω_i

Factor	w_i	ω_i
x_1	0,21	0,0729167
x_2	0,12	0,0416667
x_3	0,09	0,03125
x_4	0,06	0,0208333
x_5	0,11	0,0381944
x_6	0,04	0,0138889
x_7	0,03	0,0104167
x_8	0,3	0,1041667
x_9	0,12	0,0416667
x_{10}	0,2	0,0694444
x_{11}	0,7	0,2430556
x_{12}	0,4	0,1388889
x_{13}	0,5	0,1736111

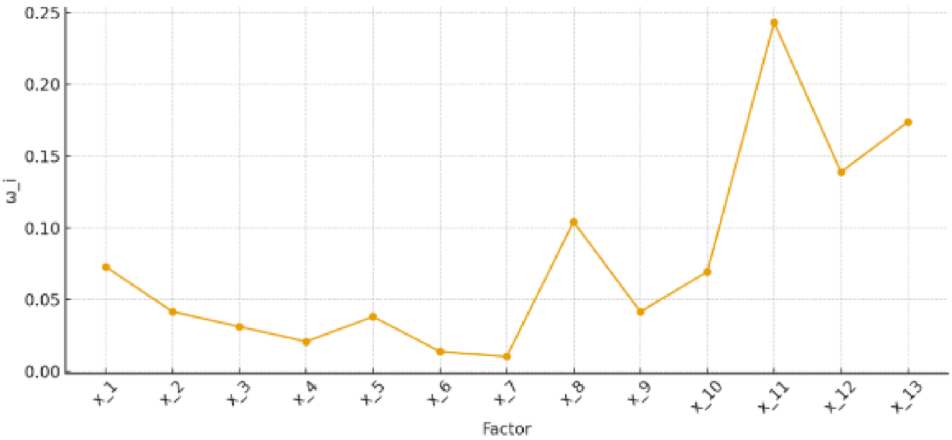

Fig. 4. The distribution of weighting coefficients

The culmination of these experiments – covering internal feature weighting, external performance validation, and computational efficiency – allows for a precise statement of the scientific contribution of this work.

5.2. Scientific novelty of the results obtained

The scientific novelty of the results obtained lies in the following:

– MMMDP has been developed, which integrates new indicators and refines the calculation of existing factors to improve the accuracy of identifying propaganda content;

– an information technology has been proposed that combines machine learning, statistical analysis, and data mining for a comprehensive assessment of the level of propaganda.

6. Discussion of results

6.1. Interpretation and accuracy assessment of the results

The publications included in the created dataset were selected in such a way as to clearly demonstrate both the presence and absence of propaganda features. This approach made it possible to ensure a more objective evaluation of the proposed models' effectiveness and to simplify the process of interpreting the results (Table 4).

Table 6. Experimental results

#	Publication Title	MMMDP	ChatGPT-4
P_1	Address by Emmanuel Macron on Europe's strategic vision	Noticeable level	Noticeable level
P_2	Speech by Marine Le Pen, presidential campaign 2017–2022	High level	High level
P_3	Trump's speech at the 2020 Tulsa rally	Moderate level	High level
P_4	Trump's speech at the 2020 rally before the completion of the vote count	High level	High level
P_5	Hitler's address to the nation (September 1, 1939)	High level	Very high level
P_6	Hitler's speech at the sportpalast	Very high level	Very high level
P_7	Introduction to linear geometry	Insignificant level	Insignificant level
P_8	The magic of mathematics	Insignificant level	Insignificant level
P_9	Ocean exploration	Insignificant level	Insignificant level
P_{10}	Apple cultivation	Insignificant level	Insignificant level

According to both models, the publication P_1 demonstrates a noticeable level of propaganda. Although it has a generally neutral and informational character – Emmanuel Macron, in his speech, conveys statements of political leaders with references to facts and quotations without emotional judgments, manipulation, or imposing a particular viewpoint on the audience – it is important for him as a politician to be persuasive, which inherently involves the use of certain propagandistic elements. Thus, both models correctly identified the publication as propagandistic; however, the MMMDP produced a higher value of the value function, which more accurately reflects the actual level of propaganda present in this publication. According to the MMDP, the publication P_2 demonstrates a moderate level of propaganda, whereas the MMMDP indicates a high level of propaganda (near the upper limit of the proposed scale Marine Le Pen's rhetoric is highly emotionally charged, identitarian in its framing and demonisation of 'the other', with minimal reliance on verifiable data. Thus, both models correctly identified the publication as propagandistic; however, the MMMDP more accurately reflects the actual degree of propaganda present in this publication.

According to both models, the publication P_3 demonstrates a moderate level of propaganda, as Donald Trump's speech contains emotionally charged language, constructs an image of the enemy ("radical left," "the crowd"), and employs "us vs. them" rhetoric along with calls to action aimed at mobilizing and polarizing the audience. Thus, both models correctly identified the publication as propagandistic; however, the MMMDP produced a higher value of the utility function, approaching the high level. This provides a more accurate reflection of the degree of propaganda present in this

Table 7. Computational complexity metrics

#	**Publication title**	**Words count**	**Processing time (in seconds)**	**Processing speed (words count/second)**
P_1	Address by Emmanuel Macron on Europe's strategic vision	307	5,01	61,2
P_2	Speech by Marine Le Pen, presidential campaign 2017–2022	272	4,46	62,1
P_3	Trump's speech at the 2020 Tulsa rally	178	2,99	59,5
P_4	Trump's speech at the 2020 rally before the completion of the vote count	219	3,45	63,5
P_5	Hitler's address to the nation (September 1, 1939)	178	2,77	64,2
P_6	Hitler's speech at the sportpalast	154	2,66	57,8
P_7	Introduction to linear geometry	129	2,21	58,4
P_8	The magic of mathematics	152	2,35	64,6
P_9	Ocean exploration	118	2,12	53,2
P_{10}	Apple cultivation	135	2,31	58,3
Average speed				60,29

publication.

According to both models, the publication P_4 demonstrates a high level of propaganda, as Donald Trump's speech contains unsubstantiated claims about massive election fraud and systematically appeals to emotions ("we will never give up," "stop the steal") to mobilize support. It also includes calls for mass action and displays of strength aimed at radicalizing the audience. Thus, both models correctly identified the publication as propagandistic; however, the MMMDP produced a higher value of the utility function, approaching a very high level. This provides a more accurate reflection of the degree of propaganda present in this publication.

According to both models, the publication P_5 demonstrates a moderate level of propaganda, as in his speech Adolf Hitler portrays the German people as victims, shifts blame to neighboring countries, and justifies aggression as a "forced response" to legitimize war and mobilize support. Thus, both models correctly identified the publication as propagandistic; however, the MMMDP produced a higher value of the utility function, approaching a high level. This provides a more accurate reflection of the degree of propaganda present in this publication.

According to the MMDP model, the publication P_6 demonstrates a moderate level of propaganda, while according to the MMMDP model, it exhibits a high level of propaganda. In his speech, Adolf Hitler employs nationalist rhetoric, simplified enemy imagery, and promises of "revival" to mobilize the audience and legitimize his regime. He appeals to emotions, uses generalizations, and engages in demagogy to manipulate public opinion and justify radical actions. Thus, both models identified the publication as propagandistic, but the MMMDP more accurately reflects the actual level of propaganda present in this publication.

According to both models, the publication P_7 does not contain propaganda, as it has a purely educational and scientific nature, presenting neutral definitions and explanations without emotional or ideological evaluation. Thus, both models correctly identified that this publication is non-propagandistic; however, the MMMDP produced a lower value of the utility function, which more accurately reflects the absence of propaganda in this publication.

According to both models, the publication P_8 does not contain propaganda, as it has a cognitive and popular-scientific nature, describing the history of the emergence of graph theory without any signs of manipulation, political, or ideological rhetoric. Thus, both models correctly identified that this publication is non-propagandistic; however, the MMMDP produced a lower value of the utility function, which more accurately reflects the level of propaganda in this publication.

According to both models, the publication P_9 does not contain propaganda, as it is scientific and informational in nature, presenting objective facts about ocean research without any emotional or ideological influence on the reader. Thus, both models correctly identified that this publication is non-propagandistic; however, the MMMDP produced a lower value of the utility function, which more accurately reflects the level of propaganda in this publication.

According to both models, the publication P_{10} is descriptive and neutral in nature, providing information about the process of apple cultivation without any signs of manipulation, ideological influence, or emotional pressure. Thus, both models correctly identified that this publication is non-propagandistic; however, the MMMDP produced a lower value of the utility function, which more accurately reflects the level of propaganda in this publication.

Thus, the introduction of additional parameters K_i^j specifically those covering messianic statements, generalizations of opponents, and the portrayal of oneself against invisible enemies – along with partial changes in the methods for their calculation [12, 14], led to a noticeable increase in the accuracy of the proposed model. Analysis of the results showed that the average values of the utility function and individual metrics increased by approximately 15,33% compared to the basic version of the model without these parameters. Therefore, the integration of new parameters enhanced the model's effectiveness and reliability, providing a more comprehensive and detailed assessment of propagandistic materials.

Furthermore, it is important to emphasize that the MMMDP demonstrated the ability to integrate both statistical and semantic parameters, creating a multi-level analytical system. This approach allows for the consideration of not only quantitative characteristics (such as repetition frequency, text length, and dissemination activity) but also rhetorical features, emotional tone, and thematic context. As a result, we obtained a tool capable of adapting to different types of information flows.

Table 5 shows that the most influential factors in terms of identifying propaganda are: messianism, opposition to opponents, opposing oneself to "invisible enemies". The least influential factors are: subjectivity of judgments, emotionally provocative patterns, unreliability of the source. However, it should be noted that this distribution of weights applies only to this dataset.

As can be seen from Table 6, the results of the two models on the validation dataset coincide by 80%. Moreover, the discrepancy is insignificant. "Moderate level" is slightly below "High level" on the scale. "High level" is slightly below "Very high level". This comparison confirms the correctness of the results obtained using MMMDP.

Table 7 shows that the average text processing speed from the validation dataset is $60,29$ words per second.

The following subsection considers the advantages and disadvantages of the proposed model.

6.2. Advantages and disadvantages of the MMMDP

The advantages of the proposed model are:

1. no human (subjective) influence on the process of calculating propaganda indicators, since only statistical data or data obtained by means of intelligent analysis are fed into the model;
2. easy model scaling by adding new indicators or removing indicators that are no longer relevant;
3. overcoming the "cold start" problem by using publications from the Forbes list of the most reputable publications, which will also ensure high accuracy of the MMMDP;
4. creation of a model's own trust rating for publication sources during the work process;
5. the correctness of the results obtained is guaranteed by the use of classical mathematical methods, methods of intelligent data analysis, and machine learning;
6. the ability to use the proposed model to train a neural network, which will then determine the level of propaganda in publications.

The disadvantages of the proposed model are:
1. the need to accumulate and store large arrays of statistical data;
2. the constant need to control the relevance of the recommendations provided;
3. the absence of a single reference scale for determining the level of propaganda in a text.

6.3. Practical application of MMMDP

1. Moderation of social networks and platforms:
   – automatic tagging of posts and comments with probable propaganda for further verification by moderators;
   – priority verification queue (high-risk $\rightarrow$ human review).
2. Journalism and fact-checking:
   – a tool for journalists that highlights text fragments with signs of manipulation (framing, exaggeration, appeal to emotions) for faster verification.
3. Public opinion analytics:
   – tracking topics and campaigns that use propaganda techniques in large social data sets; correlation with bot activity and peaks in retweets/shares.
4. Cybersecurity and intelligence:
   – identifying coordinated information campaigns (indirectly – detecting similar narratives, syntactic/lexical patterns).
5. Educational tools:
   – training systems to improve media literacy: highlighting rhetorical devices in the text and explaining why this may be propaganda.
6. Politics and research:
   – assessing the effectiveness of countermeasures (campaigns to combat disinformation) based on changes in the frequency of detected propaganda patterns;
   – an element of intent analysis of the intentions embedded in reports.

It should be noted separately that the results obtained can be used in the information war that is raging in Ukraine and around the world.

Conclusion

Within the framework of this work, the MMDP [13, 15] has been supplemented with new parameters that reflect more complex semantic and rhetorical features of texts. These features – messianism, generalization of opponents, and opposition to "invisible enemies" – are important for the formation of a multifactorial model for assessing the level of propaganda. Their integration into the system allows for more accurate detection of hidden manipulative techniques and expands the range of text characteristics that can be studied. As a result, a more comprehensive analysis tool is formed, capable of effectively detecting both overt and latent manifestations of propaganda in the information space.

The proposed MMMDP expands the MMDP and increases its accuracy by including additional features that reflect the specifics of propaganda messages at the rhetorical level.

As part of this study, both models (MMMDP and MMDP) were tested on publications with obvious signs of propaganda and clearly non-propagandistic in nature, which ensured the accuracy of the experiment.

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БАГАТОФАКТОРНА МОДЕЛЬ ВИЯВЛЕННЯ ПРОПАГАНДИ В ТЕКСТОВИХ ДАНИХ

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Виявлення елементів пропаганди в масивах текстових даних наразі є одним із основних засобів боротьби в інформаційній війні, яка відбувається в світі. В даній роботі представлено багатофакторну модель для визначення рівня пропаганди в публікації. В якості публікацій використовувалися текстові новини та дописи в соціальних мережах. Модель була створена на основі методу лінійної згортки. В даній моделі було розглянуто тринадцять показників, високий рівень кожного з яких вказує на наявність пропаганди в публікації. Значення кожного показника обчислювалося за допомогою методів статистичного та інтелектуального аналізу. Запропоновано алгоритм обчислення рівня впливу кожного фактору. Також запропонована шкала, для визначення рівня пропаганди. Для кожної з відібраних публікацій було обчислено відповідне значення функції цінності. Допустимим рівнем для функції цінності, після якого публікацію можна вважати пропагандистською, вважалося вибіркове середнє її значень для всього набору публікацій. В результаті було сформовано рекомендації щодо того, чи є кожна публікація з даного набору пропагандистською чи ні. Перевагою даного підходу є те, що кожен показник в моделі обчислюється ґрунтуючись виключно на статистичних даних та коректних математичних методах, методах інтелектуального аналізу даних та машинного навчання. Це унеможливлює вплив людини, який може бути суб'єктивним, у даний процес.

Ключові слова: інформаційні технології, пропаганда, публікація, багатофакторна модель, статистичний аналіз, аналіз даних, машинне навчання, аналіз текстів, рекомендації.