Assessing Fake News Impact on Polish Political Attitudes Toward the Ukraine War

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Abstract

In the contemporary information environment, fake news influences public opinion and political beliefs. This issue is particularly relevant during the war in Ukraine, where a significant amount of information pertains to both the events in Ukraine and Ukrainian migrants in the European Union. Poland, as a key partner of Ukraine, faces challenges related to disinformation, making the study of the impact of fake news on Polish political attitudes extremely important. This research employs advanced machine learning methods to detect fake news and analyze its impact on political attitudes. The developed model, based on a combination of text processing and classification methods, demonstrated high accuracy in distinguishing between fake and real news. The datasets used include news about the war in Ukraine and tweets from Polish users, allowing the investigation of sentiment changes in response to disinformation. The analysis revealed that fake news significantly affects political attitudes, particularly through negative emotional reactions to disinformation. The cubic spline interpolation method uncovered a nonlinear relationship between the volume of fake news and changes in political attitudes, indicating the complex nature of this influence. The research findings are significant for developing strategies to combat disinformation and enhancing public information literacy.

Keywords

cubic spline interpolation, disinformation, fake news, information literacy, machine learning, news classification, social media sentiment, text analysis, textblob, political attitudes.

1. Introduction

In the contemporary information environment, fake news has become an important factor influencing public sentiments and political beliefs. During the war in Ukraine, the issue of the impact of fake news on public opinion is particularly relevant, especially in European Union countries, where a significant amount of information pertains to events in Ukraine and Ukrainian migrants. As of June 2024, there were approximately 6.5 million refugees from Ukraine [1], with the largest number of Ukrainians under temporary protection residing in Germany – 1,347,525 people or 31.2% of the total number of Ukrainian refugees in the EU, Poland – 965,775 people or 22.4%, and the Czech Republic – 360,775 people or 8.4% [2]. In the context of numerous disinformation campaigns and attempts to manipulate public consciousness, it is crucial to understand how fake news shapes the political attitudes of citizens in host countries and which methods effectively analyze their impact.

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Considering that Poland is a strategic partner of Ukraine in the European Union and has a significant influence on regional politics, along with a large number of Ukrainian refugees in the country and active information exchange amid the Russian-Ukrainian war, studying the impact of fake news on Polish political attitudes is extremely relevant. Additionally, Poland is also facing disinformation challenges, which allows for a detailed examination of the effects of fake news on society. Advanced machine learning methods are applied to thoroughly investigate this issue, enabling not only the automation of fake news detection but also the assessment of its impact on public opinion. Through text analysis algorithms and sentiment modeling, it is possible to track changes in the political views of Polish citizens in the context of disinformation about the war in Ukraine.

This article is dedicated to assessing the impact of fake news on political attitudes in Poland, with a focus on using machine learning for analyzing and detecting fake news, as well as determining correlations between information campaigns and changes in public opinion. The results of this research can significantly aid in developing strategies to combat disinformation and enhance public information literacy.

2. Literature review

In the context of the modern information environment, where information spreads quite rapidly and continuously, it is crucial to ensure an effective mechanism for detecting fake messages. Special attention should be given to news that intentionally spreads disinformation with the aim of manipulating public opinion, undermining trust in reliable information sources, or creating social and political conflicts. Fake news can influence public sentiment, create false perceptions, and incite negative emotions among the population. Specifically, disinformation can be used for political purposes, economic gains, or to weaken social cohesion. Its effects can have long-term consequences for society, making it important to detect and neutralize such messages as quickly as possible.

In this regard, the issue of detecting and combating disinformation has gained particular relevance among researchers. Over the past few years, there has been a significant increase in scientific papers studying various aspects of this problem, including methods for automated detection of fake news, techniques for social media analysis, and effective strategies for combating disinformation. Researchers from various fields, from information technology to social sciences, are actively working on developing new approaches to detecting and eliminating false messages, highlighting the importance of this topic for modern society.

For instance, in their work, Julio C. S. Reis; André Correia; Fabrício Murai; Adriano Veloso; Fabrício Benevenuto (2019) [3] proposed a new set of features at the time and evaluated the effectiveness of existing methods and features for automatic detection of fake news. The results revealed important patterns regarding the utility and significance of various features in the process of detecting false information. The authors also provided practical recommendations for applying fake news detection methods, highlighting the challenges and opportunities in this field.

Xichen Zhang, Ali A. Ghorbani (2020) [4] investigated the negative impact of fake news on the Internet and the existing methods for its detection at that time, many of which were focused on user identification, content analysis, and context that indicated disinformation. The authors also reviewed established datasets used for classifying fake news and outlined promising directions for further research in the field of online fake news analysis.

Barbara Probierz, Piotr Stefański, Jan Kozak (2021) [5] proposed a method for classifying news based on headlines, without the need to analyze the full text. They used natural language processing (NLP) methods to analyze headlines and news texts, as well as complex classifiers, including classical ensemble methods, to achieve high classification accuracy.

Medeswara Rao Kondamudi, Somya Ranjan Sahoo, Lokesh Chouhan, Nandakishor Yadav (2023) [6] discussed fundamental theories of fake news, explored various approaches to its analysis, and examined the spread of disinformation. The authors also devoted a significant portion of their research to analyzing fake information and the methods proposed for its detection.

Abdullah Marish Ali, Fuad A. Ghaleb, Mohammed Sultan Mohammed, Fawaz Jaber Alsolami, and Asif Irshad Khan (2023) [7] examined numerous approaches for automating the detection and prevention of the spread of fake news. The authors proposed a model for detecting disinformation news that uses information from web sources and is based on a multilayer convolutional neural network and a deep autoencoder ICNN-AEN-DM. Additional information is collected from reliable online sources to confirm or refute claims presented in news content. The model uses convolutional layers along with a deep autoencoder to train a probabilistic classifier based on deep learning. The probabilistic outputs of these layers are then used to train a decision-making system by integrating a multilayer perceptron (MLP) with these outputs. Large-scale experiments using different datasets demonstrate that the proposed model outperforms other similar methods.

In addition to scientific works focusing on the use of machine learning for detecting disinformation, it is also important to consider studies dedicated to sentiment analysis of social media users and its impact on shaping public opinion. These are important as they help understand how changes in user sentiment may be related to the spread of fake news and disinformation. Additionally, public sentiment analysis provides the opportunity to identify potential threats to social stability arising from manipulations in the information space. Such research complements our understanding of the complex impact of disinformation on various aspects of public life.

For example, Nikhil Yadav, Omkar Kudale, Aditi Rao, Srishti Gupta & Ajitkumar Shitole (2021) [8] utilized a publicly available labeled dataset hosted on the Kaggle platform, detailing preprocessing steps that enhance the suitability of tweets for natural language processing methods. Each record in the dataset consisted of a pair of tweets and corresponding sentiments, allowing the authors to apply supervised machine learning methods. For sentiment analysis, the researchers proposed models based on a naive Bayes classifier, logistic regression, and support vector machines, aiming to accurately determine the emotional tone of tweets. During the analysis, tweets were classified as positive or negative, enabling the use of these classifiers in various domains, including business, politics, and analytics. By employing machine learning methods, tweets were accurately classified without the need for lexicon-based approaches, making these strategies more efficient and faster for sentiment analysis.

Yuxing Qi & Zahratu Shabrina (2023) [9] analyzed tweets about COVID-19 from major cities in England. The data underwent several cleaning stages, after which unsupervised lexicon-based approaches were applied for sentiment classification. Supervised machine learning methods were also used, including SVC, multinomial naive Bayes classifier, and random forest. The analysis revealed changes in public sentiment regarding the pandemic, with an initial increase in positive sentiments followed by a decline, while negative sentiments grew over time. The authors concluded that although the use of SVC with BoW and TF–IDF features yielded the best results with an accuracy of 71%, data limitations affected prediction accuracy. Moreover, the study demonstrates the potential of machine learning for precise sentiment analysis, although further research with larger and more diverse datasets could improve results.

Staphord Bengesi, Timothy Oladunni, Ruth Olusegun, and Halima Audu (2023) [10] investigated social media sentiment to track discussions, views, opinions, and emotions regarding the monkeypox outbreak, which affected over 73 countries. To better understand public perception of this disease, they analyzed over 500,000 multilingual tweets, categorizing them into positive, negative, and neutral using VADER and TextBlob. The study developed and evaluated 56 classification models using various algorithms such as K-Nearest Neighbor (KNN), Support Vector Machine (SVM), Random Forest, and others. The best results, with an accuracy of approximately 0.9348, were achieved using a combination of TextBlob, lemmatization, CountVectorizer, and SVM.

Neelakandan, S., Paulraj, D., Ezhumalai, P., and Prakash, M. (2024) [11] proposed an effective sentiment analysis technique for Twitter data that involves preprocessing steps including tokenization and stop-word removal, as well as using the Hadoop distributed file system to reduce word redundancy through the MapReduce technique. Emojis and other symbols are included as features for further analysis. A modified deep learning neural network (DLMNN) is then used for sentiment classification. Experimental results indicate that this model demonstrates higher performance, achieving an accuracy of 95.78% and an F-score of 95.87%, compared to other conventional methods.

Sufficient attention has been given within the scientific community to the application of machine learning methods for detecting fake news based on sentiment analysis of the public. The development of such models becomes an important part of the strategy to combat disinformation and ensure the credibility of information in the media space. These studies help better understand how fakes are related to people's emotional states and thoughts, as well as how they can alter public sentiment and perceptions of events.

Suhaib Kh. Hamed, Mohd Juzaiddin Ab Aziz, and Mohd Ridzwan Yaakub (2023) [12] proposed a new approach to detecting fake news, which includes sentiment analysis in news and comments. Using the Fakeddit dataset, which contains news headlines and comments, a bidirectional long short-term memory (Bi-LSTM) model was developed. The results showed a fake news detection accuracy of 96.77% area under the ROC curve, which is significantly higher than many contemporary methods. This confirms the effectiveness of using sentiment analysis of news and emotional comments to enhance model accuracy.

Sarita V Balshetwar, Abilash RS, and Dani Jermisha R (2023) [13] proposed a new approach to detecting fake news that uses sentiment analysis as a key feature to improve accuracy. The solution was implemented using two datasets (ISOT and LIAR) and includes feature development based on lexicon-based sentiment analysis. The study also applies multiple imputation strategy (MICE) to handle missing variables and uses TF-IDF to identify important features. Naive Bayes, passive-aggressive classifier, and deep neural network (DNN) are used for data classification. The results show a 99.8% accuracy in detecting fake news, surpassing the effectiveness of existing methods.

It is also worth highlighting the work of Ganesh Kumar Wadhwani, Pankaj Kumar Varshney, Anjali Gupta, and Shrawan Kumar (2023) [14], which focuses on analyzing public perception of the Russian-Ukrainian war through social media. Using 11,250 tweets about the war, the study applies natural language processing methods for sentiment analysis and text polarity. Machine learning models, including TF-IDF, BoW, and n-gram, were evaluated for accuracy, recall, and F1 score. The results showed that the Extra Trees Classifier (ETC) model achieved the highest accuracy of 0.84, indicating its effectiveness in classifying emotions in texts.

Unlike existing studies, which often focus on general methods for detecting fake news and their impact on public sentiment, our research aims to analyze in greater detail the frequency of fake news appearances related to the Russian-Ukrainian war, using available datasets. Our task is to analyze data from various sources to assess how frequently fake news on this topic appears in the media space. Additionally, we will investigate changes in sentiment in tweets from Polish users regarding Ukrainians to understand how disinformation about Ukraine affects their emotions and thoughts. Special attention will be given to analyzing the relationship between the appearance of fake news and changes in sentiment on social media. This will help identify possible correlations between disinformation and public sentiment, which could assist in developing more effective strategies to combat fake news.

3. Methodology

At the initial stage, a machine learning model was developed for detecting fake news based on a combination of text processing and classification methods. Initially, we used text vectorization with TF-IDF (Term Frequency-Inverse Document Frequency) to transform text data into numerical features that reflect the importance of words in a document compared to other documents in the dataset. This method reduces the weight of frequently occurring words and increases the significance of rare words that may be more informative for classification.

After text vectorization, the numerical features were passed to Multinomial Naive Bayes (MNB), a statistical classifier that estimates the probability that a news item is fake or real based on statistical models. MNB is well-suited for text classification tasks as it effectively handles frequency data and provides a high level of accuracy in cases where text features are important.

Combining these methods allowed for the creation of an effective fake news detector capable of recognizing and classifying news based on its content.

For model development, three publicly available datasets from Kaggle were used, containing thousands of news items labeled as “Fake” or “Real.” These included the Fake News Detection Dataset [15], Fake or Real News [16], and Fake News Detection Data [17]. To enhance model effectiveness, these datasets were merged into a single integrated database, creating a more representative and diverse training dataset. After data integration, preprocessing was performed, including text cleaning, noise removal, and text normalization. The combination of different datasets provided the model with a large number of examples, improving its generalization ability and accuracy in detecting fake news. Training results of the model (Table 1) on this integrated dataset achieved high accuracy in classifying news as fake or real (Accuracy: 0.98272).

Table 1

Results of the Fake News Detection Model Training

	Precision	Recall	F1-score	Support
Fake	0.98	0.95	0.91	2185
Real	0.96	0.94	0.94	2329
macro avg	0.98	0.97	0.98	4514
weighted avg	0.97	0.92	0.96	4514

From Table 1, we see that the model has high accuracy in classifying news as fake (98%) and real (96%). The model correctly identifies 95% of fake news out of all actual fake news and 94% of real news out of all actual real news. The F1-Score for both fake (0.91) and real news (0.94) is high, indicating a well-balanced model performance. The Macro Average across all classes (Fake and Real) without considering class frequencies is 0.98, with an average recall across all classes of 0.97 and an average F1-Score across all classes of 0.98. The Weighted Average, considering class frequencies, is 0.97, with an average recall considering class frequencies of 0.92 and an average F1-Score considering class frequencies of 0.96. Overall, the model demonstrates high results in both accuracy and recall for classifying fake and real news, as well as good overall performance, indicating its effectiveness in detecting fake news.

In the next stage, we used the pre-trained model to detect fake news using two available datasets from Kaggle: BBC News Articles [18], which contains 35,860 rows and 5 columns, covering the period from March 7, 2022, to July 3, 2024, and the Ukraine/Russia Conflict Dataset [19], which contains information on the ongoing conflict between Ukraine and Russia since 2014. The latter dataset includes two CSV files: one with data from 2014 to 2021 (2,990 news items) and another with data from 2018 to 2023 (96,082 news items).

For further analysis, data from these sources were integrated into a single database. From the first dataset, BBC News Articles, all news related to Ukraine and the war with Russia were selected. From the second dataset, Ukraine/Russia Conflict Dataset, the file containing data from 2018 to 2023 was used and further filtered by date starting from March 2022 to ensure relevance for analysis. Thus, the combined database enabled a detailed analysis of news content aimed at detecting fake news, considering the specifics of the war in Ukraine. Additionally, text fields were cleaned of unwanted characters, HTML tags, and stop words, and all text data were lowercased and lemmatized to bring all words to their base forms. This step is crucial for reducing the dimensionality of the text data before feeding it into the model.

For analyzing Polish political sentiments, we used the publicly available dataset Ukraine Conflict Twitter Dataset [20] on Kaggle, which includes a large number of posts related to Ukraine and the war, collected from various Twitter accounts. The collected tweets cover different aspects of the war, including political, social, and humanitarian issues, providing a current overview of public sentiments and reactions on social media. The dataset includes daily tweet records with publication dates, full text of each tweet, user data, and possibly metadata such as the number of retweets, likes, and replies. The data cover the period from February 27, 2022, to June 14, 2023, allowing tracking of sentiment and reactions in response to key events.

We used this database to analyze the political sentiments of Polish social media users regarding the Ukraine-Russia conflict. In relation to the appearance of fake news in the media, this allowed us to explore how different events and messages impact the sentiments and emotional state of the Polish public. Before conducting the analysis, tweets were cleaned of unstructured data and non-standard symbols and combined into a single DataFrame. Additionally, the data were filtered to include only tweets from Polish users, providing a more accurate tracking of specific sentiments and reactions in the context of the Polish audience. Thus, we obtained a database with 582,507 Polish tweets. For text normalization, lemmatization was applied, which facilitates accurate sentiment analysis and identification of themes and trends.

Political sentiment analysis of Polish citizens was carried out using the TextBlob library, which provides a convenient interface for performing basic natural language processing tasks such as tokenization, lemmatization, part-of-speech tagging, and sentiment analysis. Specifically, TextBlob uses polarity and subjectivity methods to determine positive, negative, and neutral sentiments in texts, which is critical for our study. Its integration with WordNet for lemmatization and easy integration with other libraries makes TextBlob an ideal choice for processing large volumes of text data and ensures high efficiency in conducting sociological and communication research.

To investigate the dependency of political sentiment changes on the frequency of fake news appearances, interpolation analysis and cubic spline interpolation methods were used. Initially, the data were divided into intervals, where each interval represents a specific range of fake news frequency. For each interval, a cubic spline was constructed to model the relationship between sentiment changes (ordinates) and the number of fake news items (abscissas). All splines are continuous and twice-differentiable in each interval, allowing for the construction of a smooth curve for analyzing political sentiment behavior in response to changes in the number of fake news items. This model adequately reflects the nonlinear nature of the relationship and provides more accurate predictions of potential sentiment changes under different conditions.

4. Results

With the integrated news database on the Russia-Ukraine conflict, and using the model trained on the training datasets, we identified 110 fake news items out of 43,811 news articles and determined their dates of appearance in the media (Figure 1).

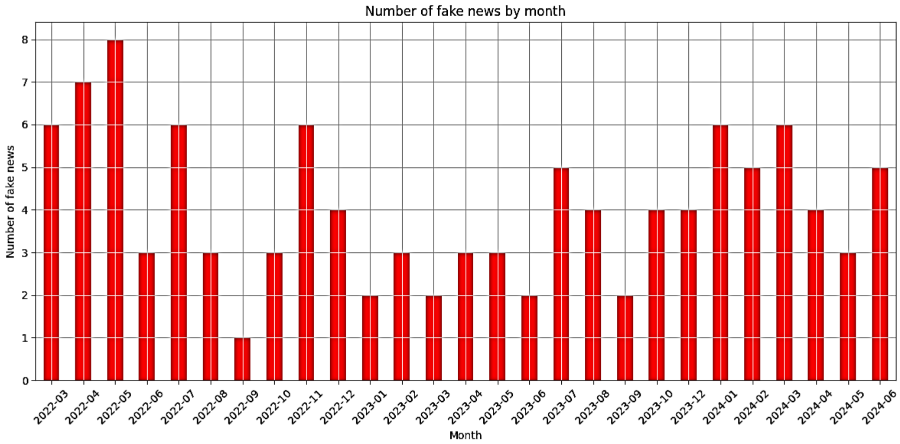

Figure 1: Fake News Count by Month.

The constructed graph clearly demonstrates the periods during which there was an increase in the number of fake news items, often coinciding with significant events related to the war in Ukraine and migration flows. These peak moments may indicate targeted information campaigns aimed at manipulating public opinion.

The identified time intervals with increased dissemination of fake information became crucial for further analyzing their impact on the political attitudes of the Polish population. This approach allows for a more detailed investigation of how fake news can influence public sentiment and lead to changes in public opinion, which is critical for understanding the consequences of information warfare in contemporary digital society.

Public sentiment is reflected not only in comments under news articles but also is actively shaped and expressed on social media. Platforms like Twitter and Facebook serve as important venues for exchanging opinions and reacting to events in real-time. Due to the large number of users and the rapid spread of information, social networks provide a more comprehensive view of public sentiment. An important feature is that these platforms allow tracking not only changes in sentiment but also the impact of information campaigns on public opinion. Thus, analyzing data from social networks is key to a comprehensive study of public sentiment.

Therefore, the next step in our research was to identify and assess the political sentiments among the Polish population in relation to events in Ukraine and the migration of Ukrainians to Poland.

As previously mentioned, we selected only tweets published by Polish users from the publicly available Ukraine Conflict Twitter Dataset on Kaggle. The main method of filtering data involved applying a conditional selection based on the values in the 'language' column of the DataFrame. This allowed us to use a simple condition to isolate only those rows where the value in the language column equals 'pl,' thereby highlighting tweets written in Polish and focusing exclusively on Polish users. Figure 2 illustrates their monthly distribution, showing trends and fluctuations in activity throughout the study period.

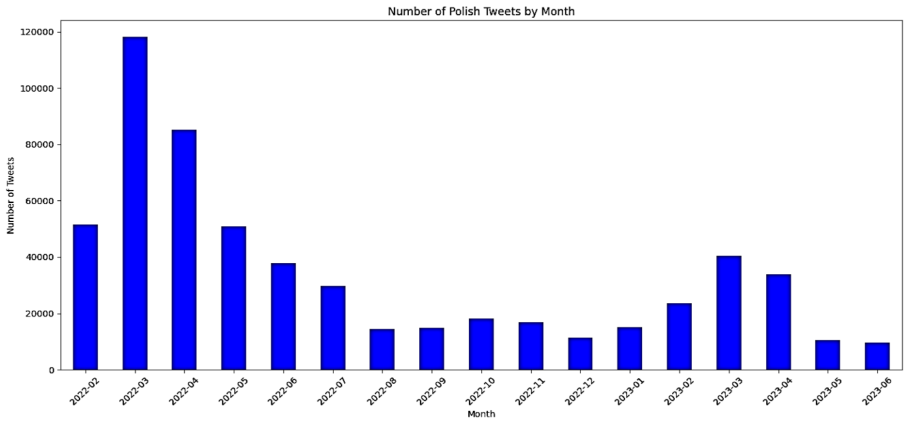

Figure 2: Number of Polish Tweets by Month.

Periods of high activity may indicate significant events or information campaigns. For example, the maximum number of tweets was recorded at the beginning of Russia's full-scale invasion of Ukraine, and an increase in user interest was noted on the anniversary of the war's start. This preliminary analysis forms the basis for further sentiment analysis, as the next task is to evaluate the emotional tone of tweets during these periods to understand how fluctuations in activity might reflect changes in sentiment or emotional state of users.

After integrating all processed data into a single DataFrame, we added a column indicating the month of each tweet's publication for convenience in further analysis. The next step was sentiment analysis using the TextBlob algorithm to assess the emotional tone of the texts. Each tweet was classified as positive, negative, or neutral based on its polarity. The data were grouped by month and sentiment categories, and proportions of each sentiment type were calculated. This allowed us to create a graph (Figure 3) that reflects changes in users' emotional sentiments over time.

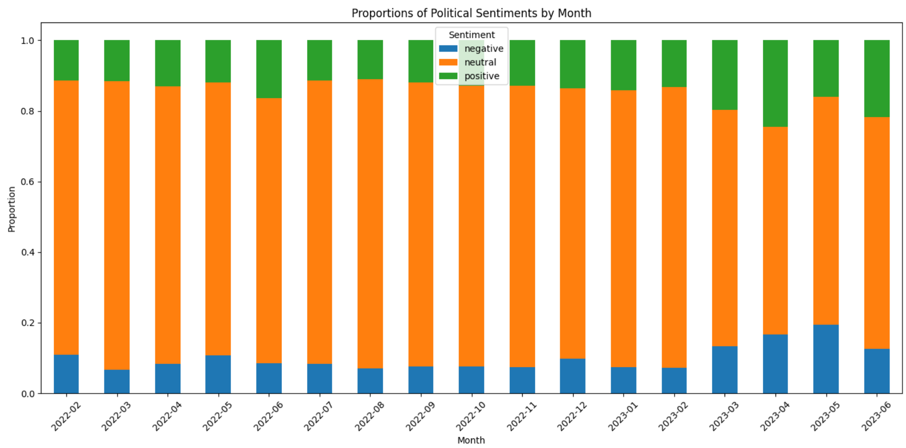

Figure 3: Proportions of Political Sentiments by Month.

The visualization in the graph illustrates how the proportion of positive, negative, and neutral sentiments changes month by month, allowing us to trace sentiment trends based on Twitter activity.

Additionally, we also created a WordCloud for positive and negative sentiments, using unique words that do not overlap between categories (Figure 4). This helps highlight key expressions that are most strongly associated with each type of sentiment.

a)

b)

Figure 4: WordCloud for Unique Positive (*a*) and Negative (*b*) Sentiments.

After a detailed analysis of the sentiments in tweets from Polish users, we proceed to evaluate the impact of fake news on changes in sentiment. Given that our data covers the period from February 27, 2022, to June 13, 2023, we will also focus on news published during the same timeframe. This will allow us to better understand whether disinformation influenced the sentiments of Poles during the specified period.

Thus, for each month, we calculated the total number of positive, negative, and neutral tweets. We then computed the average sentiment score (S) as a weighted average of positive, negative, and neutral sentiments, considering their proportions in the overall dataset:

$$S=\frac{P-N}{T}, \tag{1}$$

where P is the number of positive tweets,

N is the number of negative tweets, and

T is the total number of tweets in the month.

We calculated the sentiment changes (SC) as the difference between the average sentiment scores for the current and previous months:

$$SC_t=S_t-S_{t-1}, \tag{2}$$

where S_t is the average sentiment score for the current month t,

S_{t-1} is the average sentiment score for the previous month t−1.

Thus, a positive sentiment change value indicates that the average sentiment in the current month is higher than in the previous month, a negative value indicates a decrease in average sentiment, and a zero value means that the average sentiment remained stable compared to the previous month.

These changes in average sentiment among Polish users and the number of fake news items for each month can be visually represented in a graph (Figure 5).

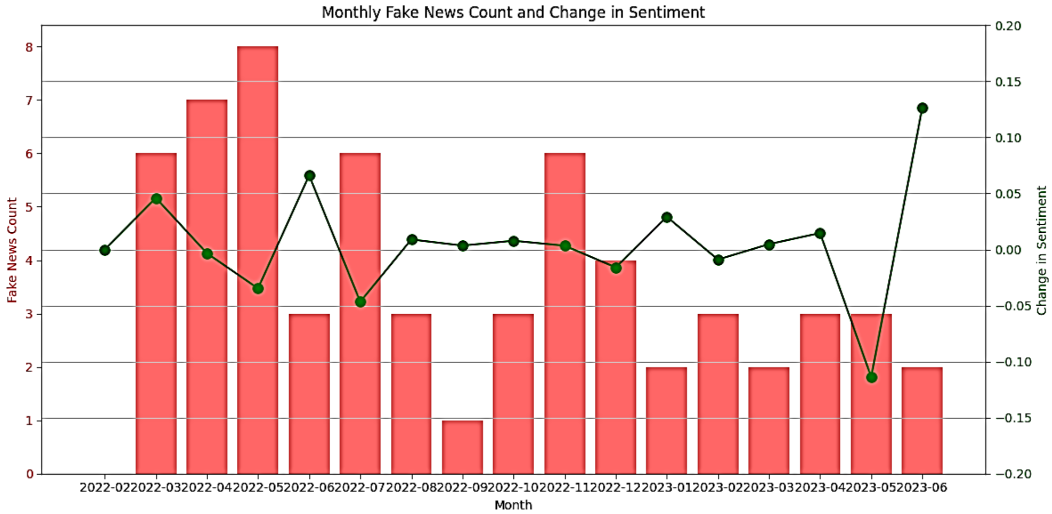

Figure 5: Monthly Fake News Count and Change in Sentiment.

From Figure 5, we can see that during the period from February 2022 to June 2023, the sentiment change indicators show an overall positive trend with fluctuations. The highest values are observed in June 2023 (0.091), which may indicate positive sentiment during this period and is accompanied by a decrease in the number of fake news compared to the previous month. Specific months, such as June 2022 (0.078) and March 2023 (0.064), also have high values, suggesting periods of improved sentiment, which are also associated with a reduction in misinformation in the media. In contrast, May 2023 shows a negative sentiment change (-0.036), indicating a temporary deterioration. Sentiment change indicators may correlate with significant socio-political events, such as news, economic or political changes, or the appearance of fake news. To better understand the reasons for these changes, it is important to analyze the events that occurred during these months.

Additionally, we calculated the changes in positive and negative sentiments using a similar approach:

$$PC_t = P_t - P_{t-1}, \tag{3}$$

where P_t is the number of positive tweets in month *t*,

P_{t-1} is the number of positive tweets in month $t-1$,

$$NC_t = N_t - N_{t-1}, \tag{4}$$

where N_t is the number of negative tweets in month *t*,

N_{t-1} is the number of negative tweets in month $t-1$.

These changes in relation to the number of fake news articles per month are illustrated in Figure 6.

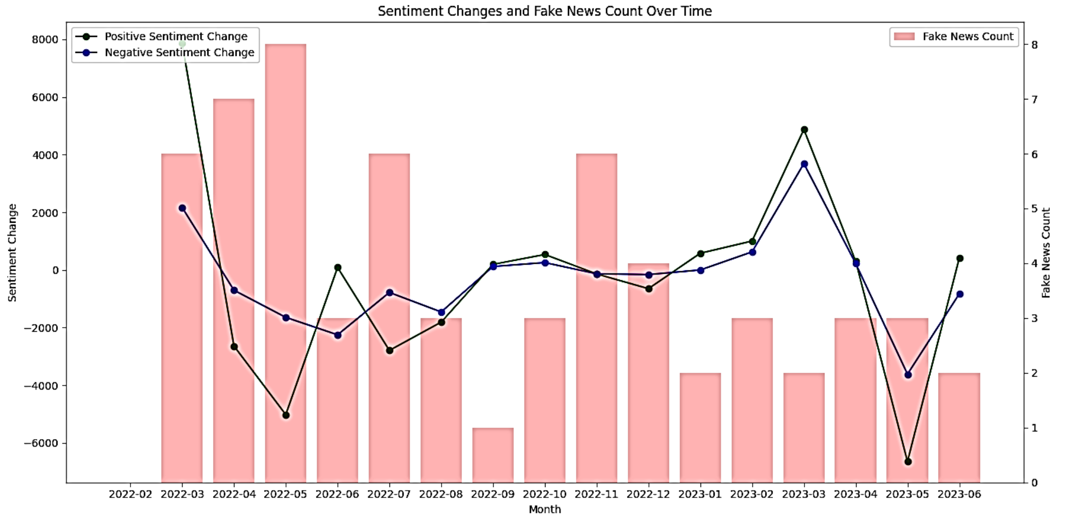

Figure 6: Sentiment Changes (Positive and Negative) and Monthly Fake News Count Over Time.

Months with the largest changes in both positive and negative sentiments often coincide with high numbers of fake news articles. For example, in March 2022, there is a sharp increase in both positive and negative sentiment changes, which corresponds with the highest number of fake news articles during this period (6 articles). Similarly, in April 2023, there was a significant rise in both positive and negative sentiments, while the number of fake news articles was at a moderate level. In some months, such as May 2022, when the number of fake news articles increased, there was a noticeable decline in positive sentiments and an increase in negative ones. This may indicate that misinformation has an impact on deteriorating sentiments among the population. Throughout the study period, there are significant fluctuations in sentiments that may be related to various social and political events. For instance, positive sentiments sharply increased in January 2023, while in May of the same year, there was the largest drop in positive sentiments and an increase in negative ones. Despite a decrease in the number of fake news articles in the second half of 2022 and the first half of 2023, sentiment changes remain unstable. This may suggest the influence of other factors, apart from fake news, on the formation of public sentiment. Thus, the data indicate a complex dynamic of the impact of fake news on public sentiments, which is important for economists and social analysts when assessing socio-economic conditions during periods of political and informational instability.

The graph showing the relationship between sentiment changes and the number of fake news articles (Figure 7) demonstrates that increases or decreases in the number of fake news articles do not always lead to proportional changes in public sentiments.

The scatter plot in Figure 7 indicates a non-linear relationship between these indicators. This complexity in the relationships suggests the need for non-linear modeling methods for a more accurate analysis of these processes.

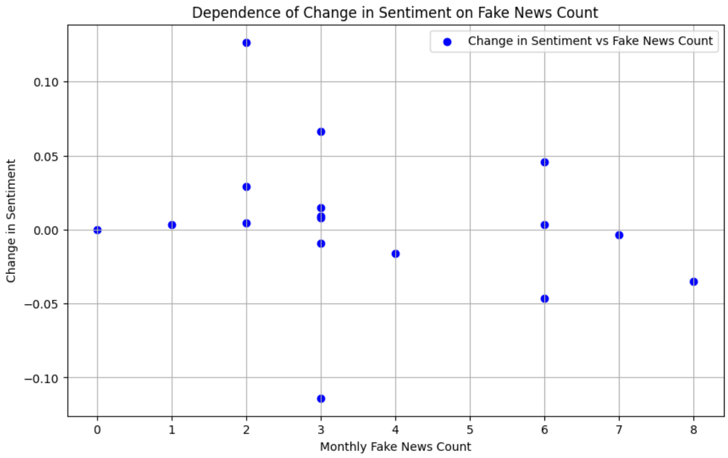

Figure 7: Dependence of Change in Sentiment on Fake News Count.

We selected interpolation analysis and cubic spline interpolation methods for this investigation due to their ability to provide high accuracy in modeling non-linear dependencies. Interpolation allows for the construction of functions that pass through specified points, while cubic splines, in particular, ensure smoothness of the curve while maintaining continuity of the first and second derivatives. This is especially important when dealing with data where sentiment changes may be abrupt or exhibit complex behavior. Cubic spline interpolation helps avoid overfitting, which can occur with high-degree polynomials, and ensures a natural transition between different intervals. These properties make this approach effective for analyzing complex socio-economic relationships, such as the impact of fake news on sentiment changes.

To build the cubic spline based on the number of fake news articles and sentiment changes, we converted monthly periods into numerical values and ensured a strictly increasing order of the data. Any duplicates or incorrect order were addressed by sorting the data.

The cubic spline plot (Figure 8) demonstrates a smooth, continuous curve resulting from interpolation between data points.

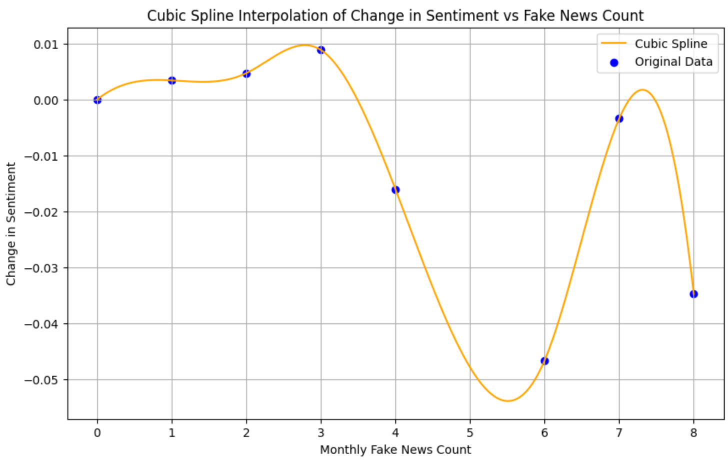

Figure 8: Cubic Spline Interpolation of Change in Sentiment vs Fake News Count

Visually, it shows how the spline smoothly transitions through each control point, providing an accurate representation of changes in the data.

The graph is divided into several intervals, each using its own cubic equation. This allows the spline to accurately reflect different trends in the data within each interval, ensuring both precision and smoothness. Additionally, we can clearly observe the transition points between intervals. The spline provides a smooth transition between these points, which is crucial for maintaining the continuity of the first and second derivatives of the function, a key property of cubic splines. The model quality assessment is presented in Table 2.

Table 2

Evaluation of the Cubic Spline Model Quality

Metrics	Values
MSE	6.0185e-36
RMSE	2.4533e-18
MAE	8.6736e-19
R-squared (R^2)	1.0000e+00

The results indicate that both the data and the cubic spline model are highly accurate. The extremely low error values (MSE, RMSE, MAE), combined with an ideal R^2 value, suggest that the model's predictions are virtually identical to the actual data. This level of accuracy indicates that the cubic spline is very effective for this dataset.

After evaluating the performance of our model through various quality metrics, the next important step is to examine the cubic spline equations that were constructed to model the relationship between the number of fake news items and changes in sentiment.

The cubic spline is a powerful interpolation tool that uses polynomial functions for each data interval. This allows the model to smoothly transition between data points, providing accurate and smooth approximation.

Given that for our study, y(x) represents changes in political sentiment among Polish social media users, and x represents the number of fake news items in the media, we will describe the equations for each interval:

Interval [0, 1):

$$y(x)=0.0031x^3-0.0103x^2+0.0107x, \tag{5}$$

On this interval, the cubic spline models the relationship with small varying coefficients. The model shows minor fluctuations in the values of y(x), corresponding to a smooth transition between the points.

Interval [1, 2):

$$y(x)=0.0031(x-1)^3-0.0011(x-1)^2-0.0007(x-1)+0.0034, \tag{6}$$

A reduction in the influence of cubic and quadratic terms is observed, reflecting smaller fluctuations in the modeling of mood changes.

Interval [2, 3):

$$y(x) = -0.0104(x-2)^3 + 0.0082(x-2)^2 + 0.0064(x-2) + 0.0047, \tag{7}$$

On this interval, the function shows a reverse effect with a negative cubic term, which may indicate a change in trend or a decrease in the influence of fake news on mood.

Interval [3, 4):

$$y(x) = 0.0064(x-3)^3 - 0.0229(x-3)^2 - 0.0084(x-3) + 0.0089, \tag{8}$$

Here, the function has a positive cubic term, reflecting an increasing effect on mood changes with the rise in the number of fake news.

Interval [4, 6):

$$y(x) = 0.0067(x-4)^3 - 0.0036(x-4)^2 - 0.0350(x-4) - 0.0160, \tag{9}$$

This interval shows a decrease in positive effects, which may indicate a reduction in the impact of fake news on mood.

Interval [6, 7):

$$y(x) = -0.0247(x-6)^3 + 0.0367(x-6)^2 + 0.0312(x-6) - 0.0467, \tag{10}$$

We observe significant fluctuations with a negative cubic term, which may indicate changes in the dynamics of the impact of fake news.

Interval [7, 8):

$$y(x) = -0.0247(x-7)^3 - 0.0373(x-7)^2 + 0.0306(x-7) - 0.0034, \tag{11}$$

In the final interval, the function has a negative cubic term, reflecting a gradual decline in the impact of fake news on mood changes.

The results show that modeling with cubic splines allows for a detailed analysis of the dynamics of the impact of fake news on public mood changes over time.

5. Conclusions

In the context of the rapid development of information technologies and the growing influence of disinformation on public attitudes, our research focuses on analyzing the impact of fake news on the political beliefs of Polish citizens in the context of the war in Ukraine. We have developed and implemented a comprehensive approach to studying this issue, integrating advanced machine learning methods for detecting fake news and a detailed analysis of their impact on public opinion, particularly through social media.

We combined multiple data sources (news and tweets) to create a unified model that assesses not only the accuracy of fake news detection but also their real impact on citizens' moods. The use of hybrid machine learning models for news classification, such as Multinomial Naive Bayes combined with TF-IDF, achieves high accuracy and reliability in detecting fake news. The use of

TextBlob for sentiment analysis ensures accuracy and efficiency in processing large volumes of textual data, which is crucial for understanding social reactions to fake news.

Our research highlights the importance of a comprehensive approach to analyzing the impact of fake news. Combining different data processing and machine learning methods provides a detailed and holistic view of the impact of disinformation on society. Future research could focus on expanding our model to include other languages and cultural contexts, as well as integrating additional data sources to improve the accuracy and universality of the analysis. Additionally, understanding the mechanisms through which fake news affects political attitudes can aid in educational campaigns aimed at combating disinformation. This includes developing educational programs and tools to enhance critical thinking among citizens.

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