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Beyond Sentiment Analysis with ChatGPT: Classifying Authors' Perspectives on Russian Topics

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Abstract

In this study, we investigate whether fluctuations in the bilateral relations between the United States and Russia influence US authors' perspectives on Russian topics expressed in their research articles. Our analysis uses a dataset of approximately 14,000 Web of Science abstracts on Russia and Russian-related topics. We developed a methodology to annotate the abstracts as negative, neutral, or positive based on the author's perceived perspective on Russia and Russian topics. These categories are based on an ad hoc definition of positivity designed for this study, extending beyond conventional sentiment analysis. Based on this positivity definition, we use ChatGPT to annotate the abstracts and compare these annotations with results from traditional sentiment analysis methods. This approach provides a novel, annotated dataset that captures authors' nuanced perspectives on Russia and Russian topics.

Introduction

The relationship between the United States and Russia has long drawn international attention, marked by recurring fluctuations in diplomatic ties. In recent years, these tensions have escalated significantly, particularly in the context of the ongoing Russo-Ukrainian war (German, 2024; Oualaalou, 2021). Sentiment analyses of official US statements reveal a persistently negative stance toward Russia, increasingly framing the two nations as geopolitical adversaries (Berger Zalmanson, 2023). Beyond changes in official statements, shifts in diplomatic relations may also shape patterns of scientific collaboration (Li & Wang, 2024) and influence the tone in which countries are referenced in scholarly discourse.

In this paper, we focus on measuring the positivity in the perspective of authors towards Russia and Russian topics in their research articles over time. We address the following research question: *To what extent do fluctuations in US–Russia diplomatic relations influence the positivity expressed toward Russia in US-authored scientific abstracts?* We hypothesize that constructive and cooperative bilateral relations encourage US researchers to adopt a more positive perspective on Russian topics. Conversely, deteriorating relations may be associated with more negative portrayals of Russia in scientific discourse.

Our methodology consists of developing a nuanced approach to measuring authors' perspectives, beyond classical sentiment analysis. First, we conceptualize and operationalize the notion of "positivity" to capture the tone of authors' perspectives across a large corpus of scientific abstracts from the Web of Science (WoS) from 1990 to 2020. Second, we implement a mixed-methods approach that combines manual annotation with automated classification using ChatGPT to classify the positivity of the abstracts. Finally, we contribute a novel annotated dataset of US-authored abstracts that reflects how scholars have framed Russia and Russian-related topics across three decades. Additionally, we discuss technical limitations associated with ChatGPT-based annotation and propose directions for future research.

Data

Our dataset includes WoS articles about Russia and Russian-related topics from 1990 to 2020, compiled through a multi-step methodology detailed by Guba et al. (2024). We pre-processed the dataset to ensure that all the articles included the necessary information for our study, such as abstracts and affiliations. First, 38% of the articles did not have standard abstracts in the metadata structure and were removed from the dataset. Next, we categorized the articles in our dataset based on types of collaboration. For cases where an author's country of affiliation cannot be determined, we classify the collaboration based on the affiliations of the remaining co-authors. For 12% of the abstracts, we were unable to assign a country of affiliation for the co-authors and, therefore, were excluded from the analysis. Finally, we obtained our final dataset with 13.938 articles. Table 1 shows the number of articles in each category based on the co-authors' affiliation.

Table 1. Types of international collaboration based on the co-authors affiliations.

	Overall *(N=13,938)*
US alone	4,219 (30.3%)
Russia alone	1,963 (14.1%)
US + RU without other countries	264 (1.9%)
US + RU + other countries	56 (0.4%)
US + other countries, without RU	405 (2.9%)
RU + other countries, without US	466 (3.3%)
Other countries alone	6,565 (47.1%)

Methodology

To assess the perspectives of US researchers on Russian topics, we adopted an ad hoc categorization framework, classifying abstracts positivity as "negative," "neutral," or "positive" based on the authors' perspectives about Russia or Russian topics. A positive perspective emphasizes a favorable presentation of Russia or Russian topics under research with an optimistic tone. A neutral perspective emphasizes a balanced and impartial presentation of Russia or Russian topics under research, with a focus on stating facts and describing data. A negative perspective emphasizes an unfavorable presentation of Russia or Russian topics under research with a critical tone. This framework was designed to capture nuanced perceptions rather than relying on traditional sentiment analysis. Figure 1 presents the annotation pipeline adopted in our methodology.

We randomly selected 1% of the abstracts (n = 140) for manual annotation by trained annotators. Three annotators annotated the abstracts independently using -1, 0, 1 to indicate whether the abstract positivity was "negative," "neutral," or "positive". The final annotation attributes the abstract as being related to a positivity when there was an agreement between at least two annotators for that positivity. The manually annotated subset served as a benchmark to validate ChatGPT's performance before using ChatGPT to classify the full dataset.

To annotate the subsample of 1% of the abstracts as well as the full dataset, we used the paid version of the ChatGPT API, employing the model "gpt-4o". We followed an ad hoc categorization framework for positivity and prompt, as detailed in the S1. The annotations produced by the ChatGPT model achieved an accuracy rate of 68% when benchmarked against the manual annotations.

Additionally, we compare the positivity annotations from ChatGPT with a traditional sentiment analysis approach. We classified all abstracts into three sentiment categories: negative, neutral, and positive. For this task, we used the paid version of the ChatGPT API (model "gpt-4o") to classify the abstracts according to the sentiment categories with a task-specific prompt, as presented in the S2.

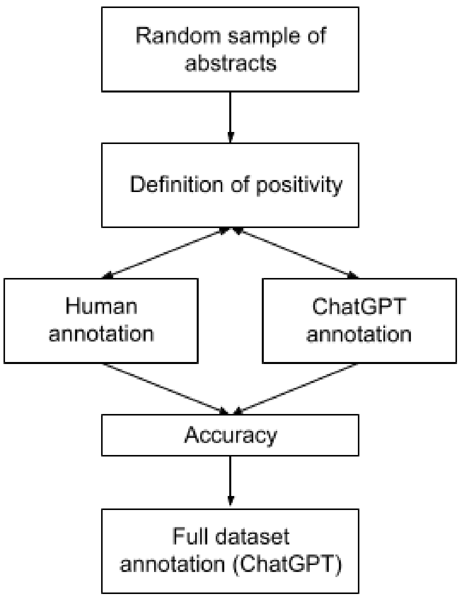

Figure 1. Abstracts positivity classification pipeline.

Preliminary results

Our preliminary results focus on describing the annotated dataset, which classifies authors' perspectives on Russia or Russian topics based on an ad hoc categorization of positivity. We also compare the positivity annotation with sentiment analysis.

Figure 2 shows the distribution of abstracts per year from 1990 to 2020 according to the positivity and sentiment classifications.

Figure 2a shows the absolute number of abstracts per year classified by ChatGPT API according to the author's positivity toward Russia and Russian topics. Overall, there is an increase in the number of abstracts over the years. Figure 2b shows the percentage of abstracts classified in each one of the positivity categories according to the ChatGPT API. While most of the abstracts are classified as neutral, 34% of the abstracts are classified as negative (see Table S3.1). The highest proportion of abstracts from the 90s and early 2000s are classified as negative.

According to the United States Department of State (2021), several key historical events defined US–Russia diplomatic relations from the 1990s to the early 2000s. In 1991, the US recognized the Russian Federation as the successor state to the Soviet Union. Another milestone was the establishment of the Bilateral Presidential Commission in 2009, aimed at fostering bilateral cooperation. Public opinion during this period also shifted. A Gallup survey (2025) reported that 60% of Americans held a favorable view of Russia in 1991, compared to 40% in 2009. However, when compared to our findings, a divergence between public sentiment and academic discourse becomes apparent. Despite high public favorability in 1991, our analysis shows a rise in the negativity of US research abstracts toward Russian topics. As shown in Figure 2b, between 1991 and 1994, approximately 40% of abstracts were classified as negative while in 2009 — when public favorability declined — the proportion of negative abstracts decreased to around 30%.

In contrast, 2014 marked a turning point in US–Russia relations, as the United States downgraded its political, economic, and military ties with Russia in response to Russia's violation of Ukraine's sovereignty and territorial integrity. This shift was followed in 2015 by a series of Western financial, administrative, and legislative sanctions that, alongside other factors, contributed to Russia's economic recession and the suspicion of cyber-interference activities in the 2016 US national elections (United States Department of State, 2021). Public opinion mirrored these tensions. By this period, favorable views of Russia among Americans had dropped to their lowest levels since the 1990s, with approximately 70% expressing an unfavorable opinion (Gallup Inc., 2025). In parallel, Figure 2b reveals a modest increase in the share of research abstracts classified as presenting a negative perspective on Russia-related topics after 2014. However, this increase did not reach the higher levels of negativity observed in the early 1990s and 2000s.

To evaluate the differences between our automated positivity classification and a standard sentiment analysis approach, we compared the results generated by ChatGPT based on our definition of positivity with those obtained through a conventional sentiment classification task. As shown in Figure 2c, the sentiment classification results from the ChatGPT API indicate that the majority of abstracts were labeled as neutral, with approximately 13% classified as negative. A detailed summary of the proportions of abstracts categorized as negative, neutral, and positive across all methods used in this study is provided in Table S3.1.

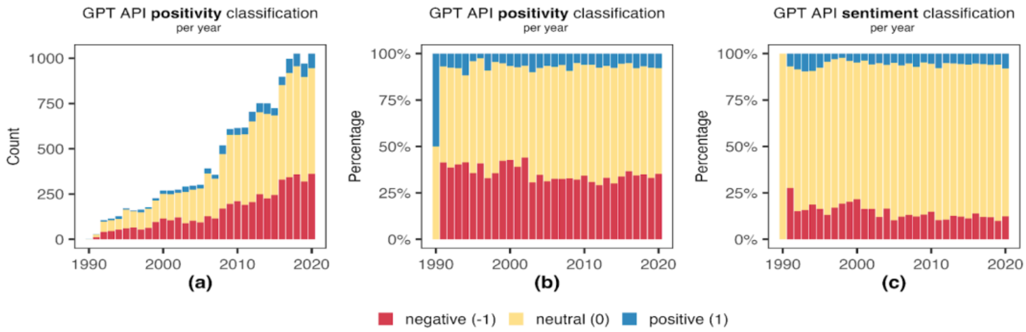

Figure 2. Yearly distribution of all the abstracts in the dataset according to the positivity and sentiment classification.

Additionally, Figures 3 and 4 illustrate the distribution of positivity scores in the abstracts disaggregated by area of study and co-authors' affiliation. As shown in Figure 3, abstracts co-authored by Russian scholars exhibit the highest proportion of negative positivity toward Russia and Russian topics. This trend is especially pronounced in papers exclusively authored by researchers affiliated with Russian institutions, which show a distinct peak in negative perspectives during the early 2000s. Figure 4 reveals notable disciplinary differences: fields such as Business, Economics & Management, Communication, History, Law, and Political Science display the highest prevalence of negative portrayals of Russia. However, temporal trends vary across disciplines. Political Science and Law consistently maintain high levels of negativity throughout the 1990–2020 period, whereas Business, Economics & Management, and History experience a decline in negative perspectives after the early 2000s. In contrast, Communication shows a marked increase in negativity, particularly in the years following 2010.

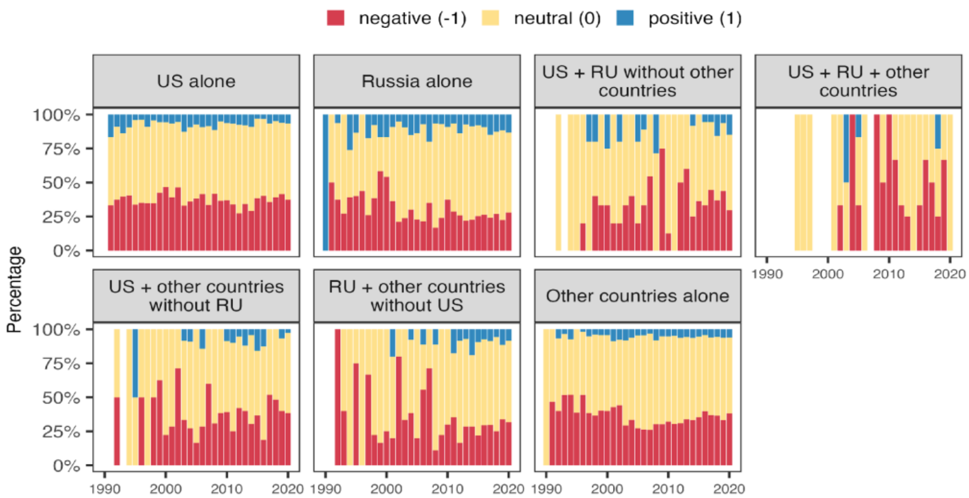

Figure 3. Yearly distribution of all the abstracts in the dataset according to the positivity by co-authors' affiliation.

Figure 4. Yearly distribution of all the abstracts in the dataset according to the positivity by area of study.

Discussion

In this work, we proposed a methodological approach to address the technical challenge of classifying nuanced perspectives in research abstracts. Specifically, we focused on capturing the degree of positivity in US authors' perspectives on Russia and Russian-related topics by developing a methodology that goes beyond traditional sentiment analysis. By integrating manual annotation with automated methods using ChatGPT, we created an annotated dataset that not only facilitates the analysis of scholarly perspectives but also serves as a foundation for examining the influence of geopolitical relations on scientific discourse.

Our preliminary findings highlight key differences between our approach and conventional sentiment analysis techniques. While traditional sentiment classification categorized most abstracts as neutral, our ad hoc criteria enabled the identification of more subtle and context-specific perspectives toward Russia. These results demonstrate the potential of AI-assisted methods to capture more nuanced authorial viewpoints.

However, our methodology has limitations. While ChatGPT offers flexibility and general language understanding, it also exhibits inherent biases such as from its training on predominantly Western-centric data, as well as output variability and potential misalignment with the nuanced nature of geopolitical discourse. To address these limitations related to ChatGPT's on training and context, future work will compare ChatGPT's performance with models such as BERT, fine-tuned on policy texts and diplomatic corpora.

Regarding output variability, ChatGPT is a non-deterministic model, meaning it can produce different outputs when given the same input across multiple runs. In this study, we report the results from a single run of ChatGPT. Future work will include additional runs and confidence interval estimations to better understand the model's variability and reliability. This statistical approach will produce more robust measures of accuracy and uncertainty.

We also aim to contextualize shifts in authors' positivity toward Russia or Russian topics by incorporating key historical events into a year-by-year analysis. This will help identify geopolitical triggers that may influence scholarly perspectives. Finally, we will examine the composition of author teams by institutional affiliation to assess how collaboration patterns—such as heterogeneous versus homogeneous groups—are associated with the positivity expressed in the abstracts.

Supplementary materials

Supplementary materials are available at the link:
https://zenodo.org/records/15213176

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