Analyzing the Discourse around Russo-Ukrainian war in Germany: Understanding Variances in Public Stances

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***Abstract*—In contemporary conflicts, public opinion is shaped not only by traditional media and politics but also by digital interactions. The 2022 Russo-Ukrainian war intensified an ongoing crisis, drawing global attention and public engagement. Social media has played a key role in mediating these responses and revealing real-time public interpretation. This study explores the online discourse surrounding the Russo-Ukrainian war on X (formerly Twitter), examining how it shapes and reflects public discourse during the conflict. Focusing on Germany, it analyzes dominant narratives, sentiments, and stances expressed on the platform, while integrating socio-economic indicators—such as unemployment rates, the Social Connectedness Index, and regional demographics—to contextualize regional variations in public attitudes and social dynamics. We employ a Large Language Model for stance detection, sentiment analysis, and topic modeling. We then apply statistical modeling to examine how these public expressions relate to socio-economic conditions and emotional tone. This study shows that public attitudes toward the Russo-Ukrainian war are emotionally complex and evolving. Negative sentiment dominates, but positive engagement around inclusion also appears. Supportive stances are more common than opposition, with a clear shift toward greater support after February 24, while opposition is more cautious and tied to socio-economic contexts. The research provides insights into the intersection of digital narratives and offline realities, offering a nuanced perspective on public discourse and its role in shaping responses to complex international crises.**

***Index Terms*—Online discourse, Public opinion, Large Language Model, Sentiments, Stance, Twitter**

I. INTRODUCTION

The conflict in Ukraine escalated significantly in February 2022 when Russia launched a large-scale military operation, following the 2014 annexation of Crimea and the onset of hostilities in Eastern Ukraine. This escalation has resulted in widespread destruction, a humanitarian crisis, and one of the largest refugee movements in Europe since World War II[1]. Over 6 million Ukrainians have been displaced, prompting international responses [1]. Germany has emerged as the leading destination country for displaced Ukrainians, serving as a primary host for these individuals. The scale and visibility of the crisis have drawn international attention, shaping both global perceptions of the conflict and the public discourse surrounding it. These dynamics have influenced narratives across traditional and digital media platforms [2], [3].

Social media plays a pivotal role in capturing and shaping public discourse during crises [4]–[7]. X (formerly Twitter) has become a significant arena for sharing diverse perspectives, engaging in debates, and expressing sentiments related to the war, its consequences, and the challenges faced by Ukrainian temporary protection seekers [8], [9]. In the digital age, it serves as a powerful channel where opinions and information spread rapidly across vast networks. X functions as a barometer of public sentiment, providing real-time insights into how individuals and communities react to geopolitical events, social issues, and policy changes [10]–[12].

Previous studies have primarily focused on analyzing the sentiments of individual users as a proxy for public opinion. However, sentiment alone often fails to capture the nuances of an individual's perspective. While sentiment analysis reflects the emotional tone—such as positivity or negativity—toward a topic, it does not necessarily reveal what position the individual takes on the issue itself [13]. In contrast, stance analysis provides a more precise understanding by identifying whether a person explicitly supports, opposes, or remains neutral toward a particular proposition or argument [12], [14]. Understanding the dynamics of sentiment and its role in shaping public stances is essential for comprehending how opinions are formed, mobilized, and amplified during humanitarian crises.

This study examines online discourses in Germany, both a host country for Ukrainian temporary protection seekers and a provider of military and humanitarian aid to Ukraine in response to the invasion [15]. Germany represents a particularly relevant case study, having also been a primary destination during the 2015 refugee crisis. However, the recent influx of displaced Ukrainians reveals notable differences from that earlier crisis. Research indicates that public support for asylum seekers has increased in the context of the Ukrainian displacement [16], largely due to the distinct demographic

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[1] https://unric.org/

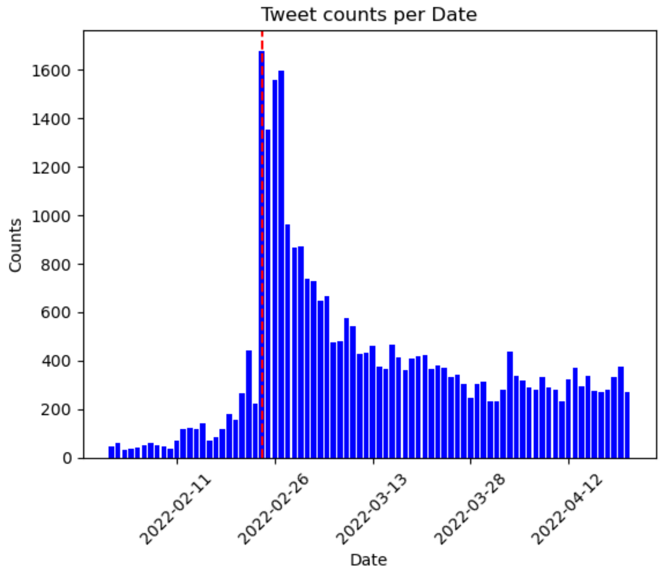

Figure 1. Number of tweets from February to April 2022 that contain hashtags related to Russo-Ukrainian war in Germany.

profile of Ukrainian refugees—most of whom are women and younger individuals [17].

The primary objective here is to gain a deeper understanding of the complex nature of public opinion regarding the Russo-Ukrainian war. The research investigates discussions surrounding the war by analyzing social media data, specifically X, to assess the dominant narratives, sentiments, and stances expressed online. Additionally, the study explores the impact of socio-economic factors, such as population size, number of protection seekers, Social Connectedness Index and unemployment rates on public stances. In particular, the study aims to answer the following research questions:

RQ1.: How is the Russo-Ukrainian war being discussed on X in Germany, and what stances and sentiments dominate the conversation?

RQ2.: How do socio-economic factors influence public opinion on Russo-Ukrainian war, as expressed through X?

Socio-economic factors provide essential context for understanding variations in opinion formation. Previous studies have demonstrated that opinions tend to be less polarized in areas with a higher percentage of foreign-born individuals [12], [18]. Similarly, economic conditions have been shown to influence public opinion. For instance, rising unemployment rates are often linked to decreased concern about environmental issues, as macroeconomic risks and business cycle fluctuations shape public attitudes toward both climate change and broader environmental policies [19]. Additionally, informal discussions with peers who share similar characteristics can reduce polarization and increase support for policies, as shown by a study on wealth redistribution [20]. These findings highlight how economic conditions and social connections collectively shape public responses during complex international crises.

To address our research questions, we integrate data from several sources. Tweets from X provide insights into public discourse, sentiments, and stances on the Russo-Ukrainian war. Socio-economic data, including regional unemployment rates, the number of protection seekers, Social Connectedness Index from Facebook, and population statistics, contextualize variations in public opinion. This combination allows for a comprehensive analysis of how online narratives interact with offline socio-economic realities. We focus on the initial phase of the Russo-Ukrainian war, spanning from February 1 to April 21, 2022. To analyze the data, we leverage OpenAI's[2] API to employ an Large Language Model (LLM) for stance detection, sentiment analysis, and topic detection. Additionally, a Multinomial Logistic Regression (MLR) model is employed to analyze the association between public stances and sentiments, while a Fractional Logistic Regression (FLR) model is used to examine the relationship between public stances and socio-economic factors. Together, these models provide insights into the interplay between digital discourse and broader societal contexts.

The structure of this paper is as follows. In Section 2, we describe the procedures used for data collection and preprocessing, including the handling of the X dataset, the Social Connectedness Index, and official statistical sources. Section 3 outlines the methodological approach, with detailed descriptions of the prompts used for the LLM and the implementation of MLR and FLR. Section 4 presents the results of our analysis, while Section 5 offers a discussion of the findings and concluding remarks.

Figure 2. An example of how a tweet containing only a URL was processed.

II. DATA

A. X data (Twitter)

For this study, tweets were collected using the X API[3]. The focus was exclusively on tweets originating from Germany. Approximately 32,000 geo-tagged tweets containing all war-related hashtags (e.g., #RussiaUkraineWar, #Ukraine, #Russia, #StopTheWar, and #NATO) were scraped and aggregated at the district level across 401 districts in Germany. By focusing on geo-tagged tweets, we ensure a precise spatial representation of online discourse related to the Russo-Ukrainian war,

[2]https://platform.openai.com/docs/overview
[3]https://developer.x.com/en/docs/x-api

enabling more localized analysis. As shown in Figure 1, there was a noticeable peak in tweet activity toward the end of February 2022, with daily tweets reaching up to 1,750. In our data, about 69% of tweets were in German, 23% in English, and the remaining tweets were in other or undefined languages. For consistency, the different languages have been retained in their original form without translation. Tweets categorized as "undefined" either contained only a URL, emojis, or user IDs. In order to make use of the information embedded in the URL, we extracted texts from the URLs by web-scraping the information as shown in the figure 2. Often the URLs were links to news articles. For this, we scraped only the title of the news article which represents the tone and information of the text [21]. For the emojis as they contain information on emotions on how a user feels about the topic discussed in the tweet, we made use of them by converting them into words, for instance, smiley face. For the rest of the categories of the information, they were excluded from further analysis as they offer no meaningful information for our analysis.

B. Social connectedness index (SCI)

In this work, we also explore the role of social connectedness across countries using the Social Connectedness Index (SCI) for 2021 from Facebook[4]. The SCI measures the strength of social ties within and across regions, providing a metric for social cohesion and connectivity that may influence both migration patterns and social media activity [22].

While the populations of Facebook and X differ demographically and behaviorally, and the SCI is not derived from X data, we use the index as a region-level proxy for the broader online social environment in which users are embedded. The rationale is that users' physical locations—derived from geotagged tweets—can approximate their regional-level social exposure and transnational ties, which the SCI captures through Facebook-based connections.

Our analysis focuses on social connectedness between German districts and Central Ukraine, including Kyiv and its surrounding regions. We hypothesize that social connectedness may shape public opinion, as individuals embedded in closely linked transnational networks may be more susceptible to influence and more likely to amplify their stances on salient issues [23], [24].

C. Official statistics

Several other data sources were also integrated into the analysis. More specifically, we gathered data on socio-economic information of each districts of Germany from the Statistisches Bundesamt (2021)[5]. These include unemployment rates (covering 16 states), number of protection seekers (individuals seeking asylum or refugee status), population size at the district level across 401 districts. The data on the number of protection seekers was provided at the level of the country of origin. Here, we aggregated the numbers by continent (i.e., Asia, Africa, and Europe), while keeping the number of protection seekers from Ukraine separate.

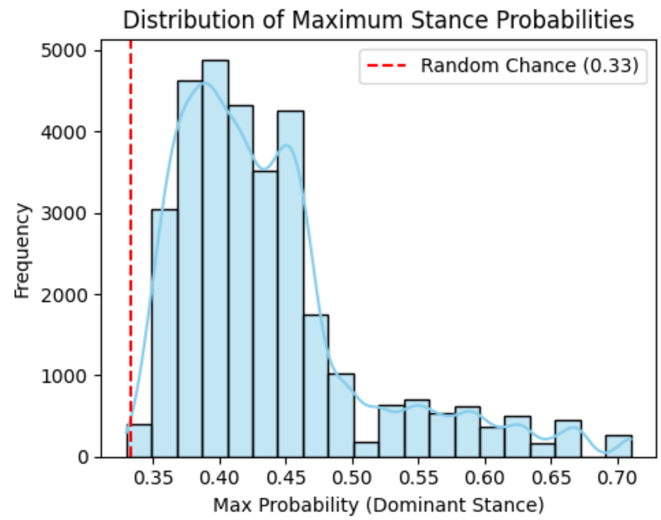

Figure 3. Distribution of maximum stance probabilities across samples (averaged over 9 runs). The red dashed line (0.33) indicates the expected maximum probability from a random guess across three stance categories.

III. METHODS

A. Large Language Model (LLM)

In this study, we leverage an LLM to conduct three key analyses of tweets: stance detection, sentiment analysis, and topic detection. These analyses were implemented using the GPT-3.5-turbo API (OpenAI, 2024[6]), enabling efficient and nuanced examination of tweets related to the Russo-Ukrainian war [25], [26].

The first step involved stance detection, where the LLM evaluated each tweet to determine whether a user is *in favor, neutral or against* a specific topic. Importantly, in favor does not imply general support for the war itself, but rather alignment with the narratives advanced by one of the involved parties. For example, a tweet supporting Ukraine's defense efforts—such as "Ukraine has every right to defend its sovereignty against aggression"—would be categorized as in favor. Similarly, a message endorsing Russian actions—like "Russia's intervention is necessary for regional stability"—would also fall into this category. This approach captures alignment with broader narratives surrounding the conflict—including those beyond direct pro- or anti-war language—such as humanitarian concerns or geopolitical framing, allowing stance detection across a wide spectrum of related discourse.

Following this, sentiment analysis was conducted to assess the overall tone of the tweets. Each tweet was assigned one of four sentiment labels: *positive, neutral, negative, or unknown*. Finally, the LLM performed topic detection by categorizing tweets into predefined thematic areas. These categories

[4]dataforgood.facebook.com/dfg/tools/social-connectedness-index
[5]www.destatis.de/
[6]https://platform.openai.com/docs/overview

spanned critical aspects such as the labor market, education, health, social inclusion, civic engagement, cultural inclusion, financial inclusion, spatial inclusion, public opinion, and the role of media[7]. This thematic classification provides deeper insights into the specific issues discussed within the social media discourse.

The prompt used to feed GPT-3.5-turbo API was the following: “User will provide you with Twitter tweets. Provide answers for all three steps independently for each tweet, without explanations. Do not print the step questions. Instead, format the output as follows: `tweet1`-[In favor, Negative, Spatial inclusion], `tweet2`-[Against, Neutral, Financial inclusion]. Step 1 - Based on each tweet, determine the user’s stance towards the Russo-Ukrainian war. Select the best-fitting stance for each tweet from the options: [In favor, Neutral, Against]. Step 2 - Identify the sentiment of the sentence for each tweet. Choose from: [Positive, Neutral, Negative, Unknown]. Step 3 - Determine the topic of the sentence, selecting only from the following options: [Labour market, Education, Health, Social Inclusion, Civic inclusion/engagement, Cultural inclusion, Financial inclusion, Spatial inclusion, Public opinion, Role of media, Unknown]”

GPT-3.5-turbo was selected due to its computational efficiency and robust language understanding capabilities. However, it is well-documented that LLMs do not consistently generate reliable outputs [27]. While constraining the temperature parameter can mitigate the stochasticity of the model’s responses, this approach can introduce a risk of systematic bias; specifically, when errors occur, they tend to be reproducible across multiple instances [28]. Consequently, in this study, we opted not to fix the temperature parameter in order to balance response variability and reduce the likelihood of persistent systematic errors. This design choice aimed to promote interpretive flexibility, enabling the model to better capture ambiguous, idiomatic, or context-dependent language often present in social media discourse. Tweets featuring sarcasm, irony, or nuanced tone can particularly be challenging for automated models, which may otherwise oversimplify or misclassify such content [29].

Owing to this variability, each analysis was repeated nine times to improve classification accuracy and consistency, with the final label assigned based on a majority vote across iterations. To assess the certainty of stance assignments, we examined the maximum stance probability for each prediction (see Figure 3). We found that in 63% of the samples, the dominant stance had a probability exceeding 0.4, suggesting a clear preference. Given that a random classifier would assign each of the three stance categories an equal probability of approximately 0.33, our results indicate that the model produces confident predictions in a majority of cases. However, the remaining 37% of cases show relatively low dominance, implying ambiguity or uncertainty in the stance classification. This ensemble-style approach helped reduce classification noise and significantly minimized the occurrence of tied results, thereby enhancing the robustness of label assignment.

To further assess reliability, we manually validated a randomly selected 1% sample of the annotated tweets. The evaluation yielded F1 scores of 74.7% for the *In favor* category, 41.1% for *Neutral*, and 67.4% for *Against*. We note that the comparatively low score for the *Neutral* category likely stems from the ambiguity and subtlety with which some users express their views. In particular, we observed that users expressing opposition often do so indirectly—through pragmatic arguments, expressions of concern about consequences for Germany, or cautionary language—rather than explicit statements. This implicit framing presents a challenge for automated classification, as it blurs the boundary between neutrality and opposition.

B. Multinomial Logistic Regression analysis (MLR)

The MLR model estimates the probabilities of multiple discrete outcomes (i.e., stance outcomes) as a function of independent variables. In this analysis, we examine how stance is associated with sentiment labels, and how this relationship changes with the onset of the war on February 24, 2022. Our model takes the following form: for each category k, where k refers to one of the categories in the dependent variable (either against or neutral), the log-odds of being in that category compared to the base outcome (in favor) is modeled as:

$$\begin{aligned}\ln\left(\frac{P(Y=k)}{P(Y=\text{in favor})}\right) &= \beta_{k0}+\beta_{k1}(\text{sentiments})\\ &\quad+\beta_{k2}(\text{dummy.2022.02.24})\\ &\quad+\beta_{k3}(\text{sentiments}\times\text{dummy.2022.02.24})\end{aligned}$$

where $P(Y=k)$ represents the probability that the dependent variable Y takes on the value k. β_{k0} is the intercept for category k. β_{k1} captures the effect of sentiment category dummies (e.g., Neutral, Positive, Unknown), with Negative as the reference category. β_{k2} represents the effect of the date dummy variable (for February 24, 2022), and β_{k3} accounts for the interaction between sentiment categories and the date dummy.

C. Fractional Logistic Regression analysis (FLR)

We employ a FLR model to investigate how socio-economic factors—including population size, the number of protection seekers from various regions, unemployment rates, and the SCI—relate to regional variations in public stance. To account for regional variation, we compute the regional average of stance categories. The regional average of each stance was computed as the share of tweets labeled against, neutral, or in favor within each region. Since these categories are mutually exclusive and collectively exhaustive, the in favor proportion was derived as the residual (1 - against - neutral), and only against and neutral were used as predictors in the regression models to avoid perfect multicollinearity. Hence, for each fractional outcome variable $y_i \in (0,1)$ (e.g., the regional average of the against stance), the model estimates the log-odds of the expected proportion as:

[7] www.migrationdataportal.org/themes/migrant-integration

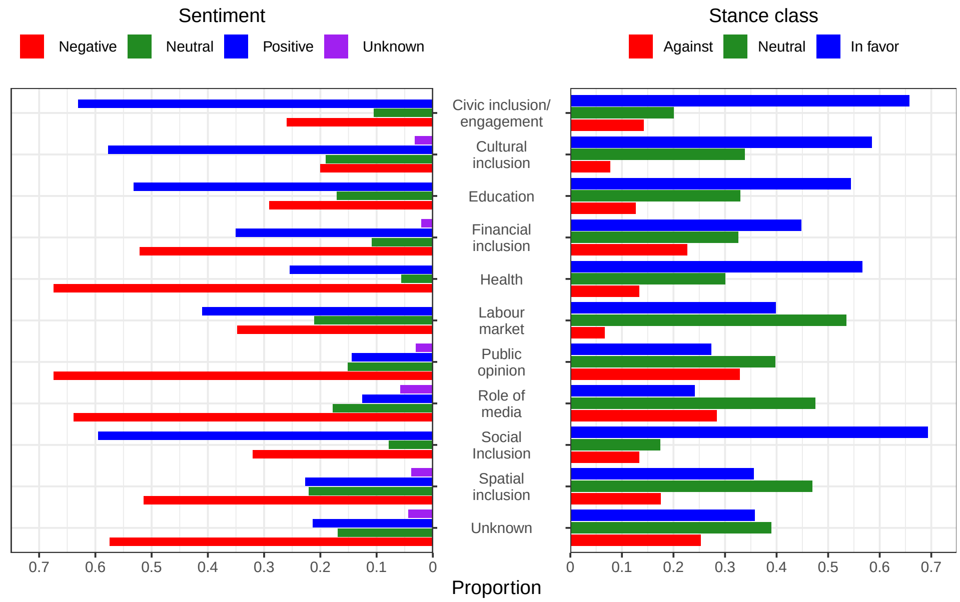

Figure 4. Bar plots of proportions of sentiment (left) and stance (right) categories per topics.

$$\begin{aligned}\text{logit}(y_i) &= \ln\left(\frac{y_i}{1-y_i}\right)\\ &= \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \cdots + \beta_k X_{ki}\end{aligned}$$

where $\text{logit}(y_i)$ denotes the log-odds of the fractional outcome for region i. β_0 is the intercept, $X_{1i}, X_{2i}, \ldots, X_{ki}$ denote the k independent variables for region i (such as population size, unemployment rate, or number of protection seekers from specific regions), and $\beta_1, \beta_2, \ldots, \beta_k$ are their corresponding coefficients.

IV. Results

A. Public Sentiment and Stances

The discourse surrounding the Russo-Ukrainian war on X in Germany reveals a diverse distribution of stances and tones. Stance detection indicates no overwhelmingly dominant perspective: 23% of tweets were categorized as against, 37% as neutral, and 40% as in favor. Sentiment analysis reveals a clear dominant tone, with 52% of tweets reflecting negative sentiment, 28% expressing positive sentiment, 16% categorized as neutral, and 4% classified as unknown. This underscores a predominantly negative tone in social media discussions about the Russo-Ukrainian war. In terms of topics, a significant number of tweets pertained to unidentified themes, followed by discussions on spatial inclusion, public opinion, civic inclusion, financial inclusion, an the role of media.

When analyzing tweets by topic, several notable patterns emerge. As depicted in Figure 4, many topics are predominantly characterized by an in favor stance, followed by a neutral stance. In most cases, the against stance does not exceed 20%, except in discussions surrounding public opinion, role of media, unknown topics, and financial inclusion. These observations underscore the general tendency for discussions to lean toward support or neutrality, with opposition being a less common stance overall. Regarding sentiment labels, the distribution varies across topics. While negative tones dominate overall, certain themes—such as civic inclusion, cultural inclusion, education, labor market, and social inclusion—stand out for their higher proportion of positive sentiment.

The interplay between stance and sentiment further highlights intriguing dynamics. Topics characterized by a predominant in favor stance often exhibit a corresponding prevalence of positive sentiment. This alignment suggests that supportive discussions are more likely to carry an optimistic tone, reinforcing the notion that favorability correlates with expressions of hope or approval. Conversely, topics with neutral or mixed stances tend to display more variability in sentiment, and the dominance of negative sentiment across many topics highlights the critical or cautious nature of public discourse. These patterns are further reflected in the MLR results predicting stance categories (against and neutral) relative to the baseline category (in favor), as presented in Table I. Two specifications are shown: Models 1 and 2 include only sentiment variables and a date dummy for February 24, 2022, while Models 3 and 4 include interaction terms between sentiment and the date dummy.

Across all models, sentiment shows strong and significant associations with stance. For instance, compared to tweets with negative sentiment (reference category), tweets with neutral sentiment are significantly less likely to express an against stance ($\beta = -2.406$) and significantly more likely to be neutral ($\beta = 1.351$). Tweets with positive sentiment are even less likely to be against ($\beta = -4.447$) and are also less likely

Table I
RESULTS OF MULTINOMIAL LOGISTIC REGRESSION ANALYZING PREDICTORS OF STANCE CATEGORIES

VARIABLES	(1) against	(2) neutral	(3) against	(4) neutral
2. Neutral	-2.406***	1.351***	-1.744***	1.643***
	(0.090)	(0.051)	(0.219)	(0.118)
3. Positive	-4.447***	-1.211***	-3.866***	-0.750***
	(0.120)	(0.041)	(0.298)	(0.089)
4. Unknown	-2.858***	1.354***	-2.168***	1.372***
	(0.251)	(0.093)	(0.517)	(0.213)
1.dummy 2022.02.24	-0.003	-0.267***	0.129**	-0.076
	(0.057)	(0.060)	(0.060)	(0.074)
2.Neutral#1.dummy 2022.02.24			-0.778***	-0.341***
			(0.277)	(0.122)
3.Positive#1.dummy 2022.02.24			-0.660**	-0.534***
			(0.312)	(0.098)
4.Unknown#1.dummy 2022.02.24			-0.828	-0.030
			(0.608)	(0.209)
Constant	0.371***	0.254***	0.259***	0.094
	(0.056)	(0.089)	(0.059)	(0.097)
Log pseudolikelihood	-26150.33	-26150.33	-26129.43	-26129.43
Observations	30,476	30,476	30,476	30,476

Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table II
RESULTS OF FRACTIONAL LOGISTIC REGRESSION ANALYZING REGIONAL AVERAGE STANCE OUTCOMES

VARIABLES	(1) against	(2) against	(3) neutral	(4) neutral
PS_Asia_2021	-2.00e-05***	-1.25e-05***	1.68e-05***	-9.91e-06***
	(1.18e-06)	(1.05e-06)	(1.48e-06)	(1.37e-06)
PS_Africa_2021	1.61e-05***	9.56e-05***	-3.34e-05***	-8.54e-05***
	(1.69e-06)	(3.46e-06)	(2.62e-06)	(3.23e-06)
PS_Europe_2021	7.81e-05***	0.0002***	-4.23e-05***	-0.000209***
	(4.94e-06)	(5.02e-06)	(6.17e-06)	(5.72e-06)
PS_North_America_2021	0.0009***	0.001***	-0.0005***	-0.0005***
	(7.43e-05)	(5.75e-05)	(0.0001)	(5.64e-05)
PS_South_America_2021	-0.000449***	-0.000141***	0.0003***	0.0002***
	(1.77e-05)	(1.51e-05)	(2.67e-05)	(2.94e-05)
PS_UKR_2021	-8.75e-05***	-0.0004***	-0.0001***	0.0003***
	(9.91e-06)	(1.25e-05)	(8.88e-06)	(1.28e-05)
population		-9.14e-07***		1.23e-06***
		(3.08e-08)		(3.96e-08)
unemployment 2021		0.004		0.091***
		(0.003)		(0.003)
SCI		-0.0005***		-0.002***
		(9.93e-05)		(9.45e-05)
Constant	-1.162***	-1.112***	-0.500***	-0.932***
	(0.006)	(0.024)	(0.006)	(0.02)
Log pseudolikelihood	-16393.3	-16015.2	-20080.6	-19655
Observations	30,476	29,948	30,476	29,948

Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

to be neutral ($\beta = -1.211$), suggesting strong alignment between positive sentiment and in favor stances. Tweets with unknown sentiment show similar patterns as neutral sentiment. As shown by the significant negative coefficients of positive sentiment in the against and neutral categories, positive sentiment is positively associated with favorability, highlighting that optimistic or hopeful tones are characteristic of supportive tweets.

The date dummy for February 24, 2022, is not statistically significant for against stances in the base model (Model 1), but becomes positive and significant in Model 3 ($\beta = 0.129$), suggesting a modest increase in oppositional stances post-war once interaction effects are taken into account. In contrast, while the date dummy is significant for neutral stances in the base model (Model 2), it becomes statistically insignificant in Model 4, indicating that the initial decline in neutrality post-war is better explained by sentiment interactions. The interaction effects highlight meaningful shifts in sentiment dynamics following the outbreak of the war. Specifically, after February 24, tweets with neutral or positive sentiment became even less likely to adopt either an against or neutral stance, relative to negative sentiment — indicating a stronger alignment with in favor stances in the post-war period and underscoring a sharpening of stance polarization linked to sentiment changes.

These results suggest that sentiment is a strong predictor of stance: although negativity dominates overall sentiment, topics with an in favor stance often exhibit a greater presence of positive sentiment. Additionally, the outbreak on February 24, 2022, appears to have shifted the relationship between sentiment and stance, with tweets expressing moderate sentiments becoming less likely to be neutral or opposed—indicating a rise in support or favorability.

B. Socio-economic factors

Table II presents the results of FLR models examining how regional-level predictors influence the average regional proportions of stance categories (against and neutral). Models (1) and (3) include only protection seekers (PS) variables by continent, while Models (2) and (4) further incorporate population size, unemployment rate (2021), and the SCI.

The number of protection seekers from different world regions is associated with distinct patterns of regional opposition. For instance, higher numbers of Ukrainian protection seekers are linked to lower levels of opposition, though their relationship with neutral stances shows some variation across models. However, these associations should be interpreted cautiously, particularly when considering multiple regions simultaneously. Notably, the patterns shift when all regional groups are included in a single regression model (see Appendix, Table III). This is primarily due to multicollinearity—high correlations between the numbers of protection seekers from different origin groups—which can cause coefficients to shrink, become unstable, or even reverse direction. While some groups may appear to face less opposition when analyzed individually, their effects can be masked or altered when other correlated groups are included. Hence, separate regressions tend to provide a more accurate estimate of each group's unique association with regional stance levels, which consistently reveal negative relationships between the number of protection seekers and both against and neutral stances.

Population size is negatively related to the against stance and positively related to the neutral stance, indicating that larger populations tend to have less opposition but more neutral positions. Unemployment rate shows a significant positive association with the neutral stance but no significant effect on the against stance. Lastly, stronger online social connections to Ukraine emerge as a significant factor in reducing opposition, emphasizing the importance of interpersonal and community-level bonds in shaping attitudes. This finding aligns with broader theories on the role of social networks in fostering solidarity and reducing prejudice [30], [31].

While most predictors exhibit statistically significant associations with stance outcomes, it is important to highlight that their estimated coefficients are generally very small (e.g., 9.91e-06). This is likely because the outcome variable represents individually averaged data, which varies on a much smaller scale compared to the larger, aggregated socio-economic predictors. As a result, the magnitude of the estimated effects appears modest, reflecting the differences in measurement scales and aggregation levels between the dependent and independent variables.

V. DISCUSSION AND CONCLUSION

In this work, we studied the online discussions surrounding the Russo-Ukrainian war by analyzing the X data in Germany. We analyzed the narratives, sentiments and stances expressed online and investigated how socio-economic factors influence public opinion on the event. There are three implications of this work.

The first is that these findings highlight the complexity of public discourse surrounding the Russo-Ukrainian war. While negative sentiment dominates much of the conversation—especially around topics like public opinion and health—it likely reflects public anxiety, fear, or moral outrage, signaling widespread emotional engagement and concern. At the same time, the presence of positive sentiment in topics such as civic inclusion, cultural inclusion, education, labor market, and social inclusion points to areas of optimism and constructive public engagement.

Similarly, the dominance of in favor stances across many topics likely reflects a broader communicative tendency: people are more inclined to express what they support than what they oppose. Rather than signaling strong ideological commitments, these expressions may simply align with familiar or personally resonant themes, without necessarily indicating a clear position on the broader conflict. The relatively low levels of opposition highlight the nuanced and often value-based nature of public responses in this discourse. After February 24, tweets with neutral or positive sentiment were less likely to adopt against or neutral stances compared to those with negative sentiment, indicating a shift toward more frequent expression of in favor stances. However, the meaning of in favor in this context is complex—it may reflect support for specific narratives or aspects of the situation rather than a simple endorsement of one side or the other.

Finally, the interplay between socio-economic factors and public opinion reveals that variables such as population size, the presence of protection seekers, and social ties to Ukraine play a significant role in shaping public attitudes and sentiments. For instance, regions with a higher number of protection seekers from Ukraine tend to show lower levels of opposition, and similarly, larger population size is also correlated with reduced opposition. Additionally, we found that areas with stronger online social ties to Ukraine are more likely to express support, highlighting how socio-economic conditions can amplify support during geopolitical crises.

An additional finding, based on manual validation, revealed that individuals expressing support tend to convey their opinions more directly. This is often seen through the use of hashtags like #StandWithUkraine or statements condemning Russia's actions and calling for an end to the war. In contrast, those expressing opposition tend not to articulate their views as explicitly. Instead, they often focus on concerns about the potential consequences for Germany or provide pragmatic advice, suggesting that intervention might escalate the situation. This cautious approach may reflect a broader reluctance to take firm public stances.

This study, while offering valuable insights, comes with several important limitations. First, our analysis is restricted to data from users on X, which introduces well-known sampling biases and limits the generalizability of our findings [32], [33]. The platform's user base may not be representative of the broader population, and the content posted may reflect a self-selected group with distinct communication styles or political orientations.

Second, our focus on tweets geotagged in Germany does not necessarily equate to capturing German public opinion. These tweets may also reflect the voices of immigrants, refugees, or displaced individuals—such as those from Ukraine—who are currently residing in Germany. As such, the dataset represents the discourse occurring within Germany, rather than the attitudes of German nationals specifically.

Additionally, to explore the relationship between socio-economic factors and public opinion, we integrated data from multiple sources and spatial levels, including the SCI, which is derived from Facebook friendships. This introduces potential inconsistencies, as the patterns of social ties on Facebook may not directly align with user engagement on X. Similarly, spatial mismatches between the scale of the predictors (often regional or state) and the outcome variable (user level) may limit the precision of the associations we observe. As a result, both the cross-platform comparability and the spatial alignment between variables remain open questions. Therefore, our use of socio-economic factors should be viewed as exploratory: while they offer suggestive evidence of how broader social and geographic contexts might relate to online discourse, they should not be interpreted as direct measures of influence or causal mechanisms.

Lastly, in this work, we employed a state-of-the-art Large Language Model to annotate tweets with stance and sentiment labels. While the annotation process was repeated nine times and manually validated, there remain notable limitations. In particular, the neutral class exhibited a relatively low F1 score of 41.1%, indicating difficulty in consistently identifying this category. LLMs are inherently black-box systems, with decision-making processes that are not fully transparent or interpretable. This opacity poses challenges in assessing how specific classification decisions are made, especially in nuanced or ambiguous cases, which in turn may impact the reliability and reproducibility of the annotations.

Despite these limitations, this study provides meaningful insights into the digital public sphere surrounding the Russo-Ukrainian war. By combining large-scale social media data with socio-economic indicators, we capture patterns of sentiment and stance that reflect both emotional responses and underlying structural factors. The integration of stance detection, sentiment analysis, and topic classification enables a more nuanced understanding of how individuals engage with conflict-related discourse, and the exploratory inclusion of social connectedness offers a novel perspective on how community-level ties might shape attitudes. For future research, it would be valuable to subdivide the in favor category into two distinct subgroups (i.e., pro-Ukraine and pro-Russia stances) to enable a more nuanced understanding of the ideological landscape and stance dynamics within the discourse. Such refinement would help reduce ambiguity and better reflect the complexity of public opinion in polarized geopolitical contexts. These findings lay a foundation for future research into the influence of digital discourse on public opinion and global events, highlighting the evolving role of online platforms in shaping collective responses to international crises.

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LIST OF CONTRIBUTIONS

Conceptualization: JK; Data collection: JK; Methodology: JK, KB; Formal analysis and investigation: JK, KB; Writing: JK.

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APPENDIX

Table III
SINGLE REGRESSION RESULTS FOR REGIONAL AVERAGE STANCE OUTCOMES (COEFFICIENTS FOR KEY VARIABLES)

Model	Outcome	PS_Asia	PS_Africa	PS_NA	PS_Europe	PS_SA	PS_UKR
(1)	Against	-2.00e-05***	1.61e-05***	0.0009***	7.81e-05***	-0.0004***	-8.75e-05***
(2)	"	-1.17e-06***	—	—	—	—	—
(3)	"	—	-6.24e-06***	—	—	—	—
(4)	"	—	—	-0.0003***	—	—	—
(5)	"	—	—	—	-3.75e-06***	—	—
(6)	"	—	—	—	—	-0.0005***	—
(7)	"	—	—	—	—	—	-2.75e-05***
(8)	Neutral	1.68e-05***	-3.34e-05***	-0.0005***	-4.23e-05***	0.0003***	-0.0001***
(9)	"	3.70e-07***	—	—	—	—	—
(10)	"	—	-6.91e-06**	—	—	—	—
(11)	"	—	—	0.0001***	—	—	—
(12)	"	—	—	—	3.21e-07	—	—
(13)	"	—	—	—	—	0.0002***	—
(14)	"	—	—	—	—	—	-3.85e-05***

Robust standard errors in parentheses omitted for brevity. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$