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Unravelling Dynamics of Migrant Solidarity: A Comprehensive Analysis of Social Media Discourse Amidst Crisis

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Abstract:- Expanding upon our prior research endeavors, our study delves into the dynamics of communal support towards migrants and refugees in the wake of transformative events, focusing specifically on the period before and after the emergence of the COVID-19 pandemic. We achieve this through the meticulous collection and examination of an extensive and original dataset composed of tweets associated with migration. Our primary objective entails the evaluation of alterations in social cohesion and solidarity expressed towards migrants during these distinct temporal phases.

To initiate this investigation, we meticulously assess a corpus of more than 2000 tweets, deciphering the presence of either supportive or adverse sentiments towards immigrants. This is accomplished by employing two distinct approaches for annotation: one reliant on the expertise of individuals and the other soliciting contributions from the general public. Building upon these annotated tweets, we develop a Long Short-Term Memory (LSTM) model, enriched by a multitude of data augmentation strategies. Impressively, the performance of this model approaches the upper echelons of human accuracy. This finely-tuned model serves as the foundation for the subsequent automated labeling of over 240,000 tweets spanning the period from September 2019 to June 2021.

Through a meticulous analysis of these automated labels, we elucidate the evolving landscape of migrant-oriented sentiments over this critical period, encompassing both the prelude and the aftermath of the COVID-19 outbreak. Notably, our findings underscore the escalating prominence and contentiousness of expressions of solidarity towards migrants during the initial phases of the pandemic. However, as the timeline progresses, this solidarity seems to recede in significance, with a slight dip in tweet volume below levels observed in more standard contexts by the summer of 2021. Interestingly, a subset of tweets linked to the COVID-19 crisis displays an elevated proportion of sentiments opposing solidarity.

In a significant contribution to the field, we also address the potential pitfalls associated with scrutinizing trends in social cohesion. For instance, we underscore how the balance between solidarity-affirming and anti-solidarity sentiments can be influenced by various factors, such as the choice of sampled tweets, the linguistic characteristics of these tweets, the national identification of Twitter users (whether known or anonymous), and the meticulous selection of pertinent tweets.

Keywords:- *Solidarity, Crisis, Social Media, Long Short-Term Memory(LSTM), Random Forest, Social Dynamics, Trend Analysis, Societal Responses, Anti-Solidarity.*

I. INTRODUCTION

In times of crisis, the online realm becomes a crucial space where shifts in pro- or anti-social behaviors are displayed, carrying significant implications for both societal cohesion and political mobilization. This study centers its focus on the realm of Twitter, employing the context of expressions concerning migrant solidarity and anti-solidarity as a lens through which to unravel these intricate dynamics. Social solidarity, a concept denoting individuals' willingness to extend aid and share resources beyond self-interest, serves as a cornerstone of pro-social conduct that upholds societal functioning in moments of turmoil. Conversely, the manifestation of anti-solidarity sentiments directed towards migrants and refugees represents a unique facet of antisocial behavior, encompassing actions that lack empathy and consideration for the well-being of others. This interplay is pivotal, as the fabric of a well-operating society hinges upon the predominant absence of such antisocial tendencies. Fundamental to these conceptualizations is the assessment of individuals' altruistic orientations or rejections thereof, particularly concerning out-groups such as migrants and refugees.

Amid the backdrop of the ongoing COVID-19 crisis, the significance of online media has surged, especially during prolonged lockdowns that confined individuals to their homes. This digital landscape has evolved into a conduit for engaging with the external world, consuming news, and voicing political viewpoints. Correspondingly, recent investigations suggest an upswing in both anti-social behaviors and their digital counterparts during times of crisis. These trends are observable across both online platforms and real-world contexts. Yet, the durability of these dynamics and their intricate relationships remain shrouded in uncertainty. Within this research sphere, the integration of Natural Language Processing (NLP) techniques to dissect online pro- and anti-social behaviors within textual content from social media platforms emerges as a potent tool. Such an approach holds promise in providing insights that can illuminate social scientists and policymakers, supplementing conventional survey-based evidence that probes potential threats to social cohesion and the vulnerability of marginalized social clusters.

Presently, endeavors to comprehend online pro- and anti-social behavior confront several limitations that temper their conclusions with bias. These deficiencies underscore the significance of our current study, which seeks to rectify such shortcomings. By engaging a comprehensive exploration of sentiments present in a textual dataset extracted from Twitter, our research endeavors to offer a nuanced and accurate portrayal of the dynamics surrounding migrant solidarity and anti-solidarity expressions. Such an inquiry holds the potential to refine our understanding of the underlying mechanisms that steer individuals' responses to crises within digital spaces.

To address these critical gaps, this study embarks on a multifaceted investigation that involves the meticulous annotation of over 2000 tweets, a process that categorizes sentiments as either aligned with solidarity or in opposition to it. Leveraging a two-pronged approach for annotation involving both domain experts and crowdsourced contributors, our methodology aims to yield robust and comprehensive assessments. These annotated tweets subsequently form the basis for training a Long Short-Term Memory (LSTM) model. Augmented with diverse strategies, this model's performance nearly rivals human-attained accuracy. By leveraging the precision of this model, we conduct automated labeling for a staggering 240,000 tweets spanning the timeframe from September 2019 to June 2021.

In analyzing the automated labels, our study strives to shed light on the temporal trajectory of sentiments pertaining to migrant solidarity and its counterpoint during the prelude and progression of the COVID-19 crisis. Noteworthy shifts in the prominence and contestation of these sentiments are brought to the forefront of our analysis. Early stages of the pandemic see an upsurge in the saliency of migrant solidarity expressions, which, however, wane in importance since the latter part of 2020, with tweet volumes dipping slightly below levels witnessed prior to the crisis by the summer of 2021. Interestingly, a subset of tweets associated with the COVID-19 crisis manifests an increased ratio of anti-solidarity sentiments.

Moreover, our study contributes a critical layer of reflection upon the challenges inherent in dissecting trends within social cohesion dynamics. We underscore the intricate interplay of factors such as language, national identification of users, and the precise selection of tweets, all of which influence the balance between expressions of solidarity and anti-solidarity.

II. LITERATURE SURVEY

“Mediating solidarity, Global Media and Communication” by N. Fenton [1], the rise of alternative political media and identity politics has led to political fragmentation, challenging traditional allegiances. Postmodern theorists view fragmentation positively for recognizing diverse political desires and debunking homogeneity. Yet, political efficacy requires more than diversity; solidarity is essential for a viable political community. While new communication technologies mediate global solidarity, linking online politics to real-world movements remains a challenge.

“The emotional antecedents of solidarity in social media crowds, New Media & Society” by D. Margolin and W. Liao [2], this study investigates how emotional expression within social media crowds affects their solidarity dynamics. Focusing on crowds discussing ongoing National Football League games, the research utilizes game outcomes as quasi-random influences to mitigate confounding variables. Findings reveal that crowd participation is self-sustaining over a week but can be triggered or dampened within an hour based on expressed emotions. Anger fosters participation, sadness hinders it, while positive emotions and anxiety have complex connections to engagement. This sheds light on emotional drivers of crowd behavior and their impact on sustained participation and solidarity dynamics.

“The role of grassroots food banks in building political solidarity with vulnerable people” by S. Koos and V. Seibel [3], Amid Spain's economic crisis, food banks emerged as emergency solutions, criticized for perpetuating dependency and inequality. However, in Madrid post the 15M movement, grassroots food banks transformed assistance into solidarity, particularly in Tetuán. Political and interpersonal solidarity thrived within these banks, fostering inter-recognition and identifying the roots of recipients' hardships. This cultivates a sense of cohesion, challenging inequality and stigma inherent in traditional charity models. Grassroots food banks not only provide aid but also forge new solidarity avenues, countering hierarchical relationships found in formal food banks, thus promoting social inclusion.

“Stereotypical gender associations in language have decreased over time, Sociological Science” by J. J. Jones, M. R. Amin, J. Kim, and S. Skiena [4], Utilizing a vast digital book collection, we track the evolution of gender stereotypes in written English from 1800 to 2000. Employing word embeddings, we quantify male gender bias across four domains: career, family, science, and arts. While gender associations have diminished over time, biases persist. Career and science terms exhibit positive male gender bias, while family and arts terms show negative bias. We asecond shift, finding partial evidence. Traditional gender ideologies are embedded in English texts, but their strength appears to wane across time.lso examine shifting associations reflecting the

"Norms of online expressions of emotion: Comparing Facebook, Twitter, Instagram, and WhatsApp, New Media & Society" by S. F. Waterloo, S. E. Baumgartner, J. Peter, and P. M. Valkenburg [5], This study aimed to explore emotional expression norms on social media, focusing on perceived appropriateness of six emotions (sadness, anger, disappointment, worry, joy, and pride) across four platforms. Data from 1201 young Dutch users (15-25 years) in March 2016 revealed positive expressions were generally seen as more fitting than negative ones across platforms. Differences emerged among platforms: negative emotions were most acceptable on WhatsApp, followed by Facebook, Twitter, and Instagram. Positive emotion expression's appropriateness ranked highest on WhatsApp, then Instagram, Facebook, and Twitter. Gender differences existed, while age variations were limited.

III. METHODOLOGY

The exploration of social solidarity, a vital pro-social behavior, has been a consistent theme in social sciences, tracing back to thinkers like Rousseau and Durkheim. While past research predominantly employed surveys and qualitative methods, the emergence of computational social science has introduced novel approaches, like integrating solidarity into Natural Language Processing (NLP). Notably, computational studies have investigated crises such as the European Migration Crisis and the Financial Crisis, spotlighting media discourse disparities and solidarity discussions across various platforms. However, these investigations primarily focused on mainstream media, while social media offers unique avenues for contestation, reevaluation, and diversification of narratives surrounding solidarity claims.

➢ *Existing System:*

The Random Forest algorithm is a widely used machine learning technique that enhances prediction accuracy by combining multiple decision trees. The mechanics of a Random Forest model are as follows:

- *Ensemble of Decision Trees*: A Random Forest comprises multiple decision trees, each trained on a distinct subset of training data (a bootstrap sample), using a subset of features at each split. This controlled randomness prevents overfitting and bolsters the model's generalization capacity.
- *Training Process*: Training involves these steps: a. Randomly select training data subsets (with replacement) to form bootstrap samples. b. Randomly choose feature subsets for decision tree splits. c. Construct decision trees using the bootstrap samples and chosen features, recursively partitioning data based on feature values. d. Repeat (a) to (c) to create multiple trees.
- *Prediction*: When predicting with a trained Random Forest model, each decision tree autonomously predicts the target variable. For regression, predicted values are averaged for the final outcome. For classification, the ensemble applies voting (majority class) or averaging (probabilities) to determine the final class label.

➢ *Random Forest:*

The widely embraced machine learning ensemble technique, Random Forest, is adeptly applicable in both classification and regression undertakings. Functioning as a variant of decision tree-based models, it orchestrates multiple decision trees harmoniously for predictive tasks.

➢ *Core Aspects of Random Forest:*

- *Decision Tree Fusion*: Random Forest orchestrates diverse decision trees to culminate in predictions. Each tree is trained on a distinct random data subset.
- *Prediction Aggregation*: The ultimate prediction outcome stems from aggregating the predictions of all individual trees.
- *Random Subset Training*: The model assembles decision trees, each cultivated on a random data subset (employing bootstrapping), while every split integrates a randomly selected subset of features.
- *Embedding of Randomness*: This deliberate incorporation of randomness mitigates overfitting, thereby elevating the model's capacity to generalize beyond training data.

- *Outcome Derivation*:

For concluding predictions, the prevailing approach involves either majority voting or the averaging of predictions engendered by the entire tree assembly.

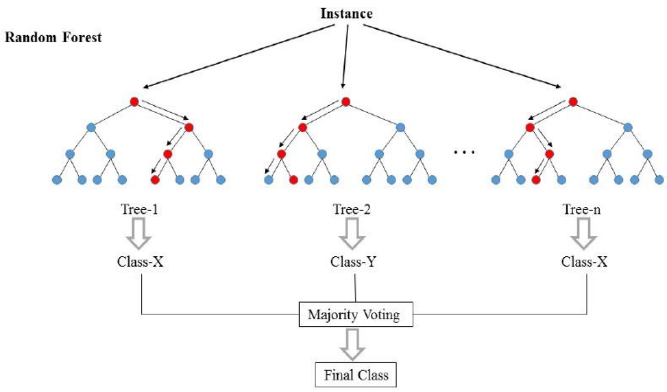

Fig 1: A Random Forest Overview

Within our methodology, the potent Random Forest technique holds sway. Employed for both classification and regression, it leverages its ensemble of decision trees to extrapolate predictive insights. This model is especially effective for our investigation, wherein we explore the evolving dynamics of sentiments and expressions of solidarity within the context of crisis scenarios. By training individual trees on diverse subsets of data and combining their outcomes, we foster a holistic understanding of these intricate patterns. Furthermore, this approach integrates randomness purposefully, countering the pitfalls of overfitting that could potentially taint our results. The collective wisdom of these decision trees, facilitated by the Random Forest paradigm, fortifies our endeavor to discern the underlying sentiments and solidarity expressions in digital discourse during periods of crisis.

- *Disadvantages:*
- Single trees may be visualized as a sequence of decisions
- A forest is less interpretable than a single decision tree
- Lack of interpretability
- Computational complexity
- Overfitting

- *Proposed System:*

An LSTM (Long Short-Term Memory) model represents a type of recurrent neural network (RNN) architecture meticulously engineered to grapple with prolonged dependencies, effectively mitigating the vanishing gradient problem inherent in conventional RNNs. Its widespread applicability encompasses sequence data manipulation tasks, spanning domains like natural language processing, speech recognition, and time series analysis.

- *LSTM Algorithm for Sequential Data Analysis:*

The Long Short-Term Memory (LSTM) algorithm, a variant of recurrent neural network (RNN) architecture, specializes in processing and comprehending sequential data. Its design overcomes the vanishing gradient problem and facilitates the assimilation of long-range dependencies in the data.

- *LSTM Workflow Highlights:*
- *Data Setup*: Input data for LSTM demands sequencing, encompassing text, time series, or similar formats. Data is divided into input and corresponding output sequences.
- *LSTM Structure*: Comprising multiple memory cells, each with an internal state, LSTM integrates three core elements: input gate, forget gate, and output gate. These components wield control over information flow, dictating storage, oblivion, and emission.
- *Forward Progression*: The LSTM algorithm processes input sequences incrementally. With each time step, input enters the LSTM network, and the model computes outputs based on input, prior hidden state, and preceding memory cell state. Gates manage information movement within memory cells
- *Backpropagation Through Time (BPTT)*: Post forward movement, the algorithm computes the variance between predicted and actual outputs, translating to loss computation. BPTT technique propels the error back in time to update LSTM network weights, thereby minimizing loss
- *Training Phase*: LSTM undergoes training through iterative weight adjustments, facilitated by gradient descent optimization techniques (e.g., stochastic gradient descent, Adam, RMSprop). This iterative process seeks to minimize the loss function by refining model weights and biases
- *Prediction Capability*: Post training, the LSTM algorithm transitions into predictive mode. When provided with new input sequences, it generates corresponding output predictions. By propelling input through the network, it derives outputs at each time step

Within our methodology framework, the LSTM algorithm emerges as a pivotal instrument. Tailored to our research objectives, it scrutinizes the unfolding sentiment and solidarity discourse dynamics during crisis periods. Employed to assess large-scale data, the LSTM model navigates through the intricacies of sequence-based content, enabling the identification of patterns, trends, and shifts. Via continuous training, it learns to capture the nuanced interplay between evolving sentiments and the expression of community support. The technique's adaptability for diverse types of sequential data fortifies our exploration across the temporal dimensions, enhancing our comprehension of the emotional landscape and solidarity dynamics amidst crises

- *Salient aspects of LSTM models include:*
- *Memory Cells*: The fundamental cornerstone of an LSTM model resides in its memory cell. This dynamic entity facilitates information retention and retrieval across extensive sequences. Featuring a self-loop connection, the memory cell ensures unimpeded temporal information flow, thereby adeptly capturing long-range dependencies
- *Gate Mechanisms*: LSTM models incorporate gate mechanisms to regulate internal information flow within memory cells. Three pivotal gate types comprise this architecture:
- *Forget Gate*: Assesses the need to discard specific memory cell contents. Informed by prior hidden states and current inputs, it yields per-element values in the memory cell, signifying the degree of information to relinquish
- *Input Gate*: Determines incoming data for memory cell storage. It discerns pertinent segments of ongoing inputs and previous hidden states for inclusion, culminating in a provisional value designated for memory cell augmentation
- *Output Gate*: Dictates the information to be emitted from the memory cell. Synthesizing contemporary inputs and preceding hidden states, it adjudicates the constitution of information to be conveyed as the present hidden state
- *Backpropagation Through Time (BPTT)*: A vital training method for LSTM models, BPTT harmonizes with the sequential data context. This variant of backpropagation propagates error gradients over temporal horizons, equipping the model to grasp the complete sequence context
- *Stacked LSTM*: In certain scenarios, the strategic layering of multiple LSTM tiers enriches model depth. Each stratum absorbs the output of its precursor, thus enabling intricate representation learning
- *Training and Optimization*: Conventional training of LSTM models leverages gradient-based optimization schemes, encompassing stochastic gradient descent (SGD) and advanced variants like Adam and RMSprop. The overarching objective entails loss function minimization, quantifying disparities between model predictions and actual values
- *Applications*: LSTM models find successful deployment across manifold tasks. Natural language processing arenas include language modeling, sentiment analysis, and machine translation. Furthermore, they empower speech

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recognition systems, furnish time series forecasting capabilities, and facilitate anomaly detection.

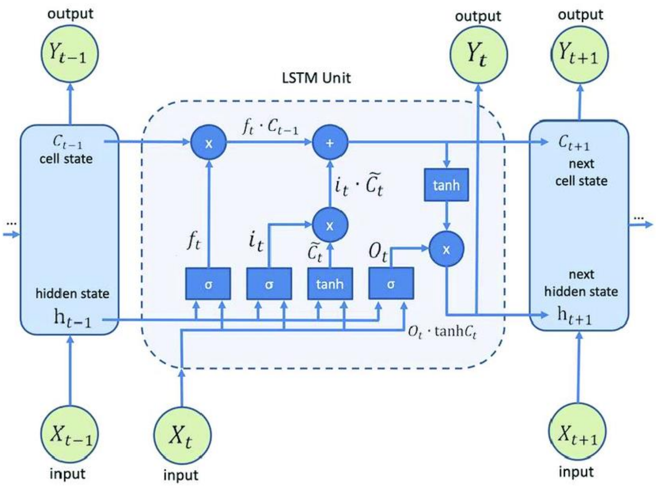

Fig 2: Basic structure of the LSTM model

In our methodology, we harness the potential of LSTM models, intricately designed for capturing intricate sequential patterns, by applying them to our large-scale dataset. By exploiting their inherent capacity to handle long-term dependencies and nuanced context, we aim to assess the evolving dynamics of sentiments and solidarity expressions within the scope of our research domain. Through diligent training using advanced optimization techniques, we intend to unravel the intricate relationships that underlie the observed trends and changes in social media discourse over time. This cutting-edge approach bolsters our endeavor to provide a comprehensive understanding of the interplay between emotions, sentiments, and communal support during crisis periods.

- *Advantages:*

- Network is a type of RNN
- Learning sequential data prediction problems
- LSTM also has some layers which help it to learn and recognize the pattern for better performance
- Capturing Long-Term Dependencies
- Handling Variable Length Sequences
- Learning Complex Temporal Patterns
- Handling Noisy and Missing Data

For this project, we have designed following modules

- *Dataset:*

For German tweets, tweets without specified Twitter account locations were also included. Tweets were gathered exclusively based on specific hashtags relevant to our topics: refugee and financial solidarity.

- *Pre-processing:*

We employ the unforeseen initiation of the COVID-19 crisis, commencing with the initial European lockdown in late February to early March 2020. This period enables the analysis of how social solidarity discourse evolved before and during the pandemic. The pre-COVID-19 phase establishes a baseline against which pandemic-related dynamics can be assessed. Ensuring comparability, we maintain a consistent baseline of solidarity discussion prior to and post the pandemic's outset.

- *LSTM Algorithm:*

LSTM, denoting long short-term memory networks, constitutes a subset of Deep Learning techniques. This variant of recurrent neural networks (RNNs) specializes in grasping long-range dependencies, especially applicable to sequence prediction problems. Among RNN types, LSTM networks are the most prevalent. The crux of LSTM involves memory cells and gates (including the forget and input gates), controlling memory cell contents through input and forget gate modulation.

- *Training:*

Researchers, particularly those engaged in NLP or data science, often tailor their machine learning models to suit the task, like analyzing English-only tweets. However, this decision can potentially introduce bias to findings. Various factors can sway results, influencing the conclusions drawn from online discourses.

- *Analyzing Accuracy on Test Set:*

Our model achieved a commendable accuracy rate of 93.75% on the test dataset.

Within our methodology, we draw on meticulously curated datasets comprised of tweets. Our focus lies in understanding the transformation of sentiments and solidarity expressions, pinpointing how they evolved preceding and during the COVID-19 crisis. By adopting LSTM-based Deep Learning techniques, we harness the capability of these networks to grasp intricate patterns in sequence-based data. This approach aligns with the paradigm shift introduced by the pandemic and its influence on online discussions. Notably, the pre-COVID-19 period serves as a benchmark, ensuring robust comparisons across these distinctive temporal phases.

- *System Architecture:*

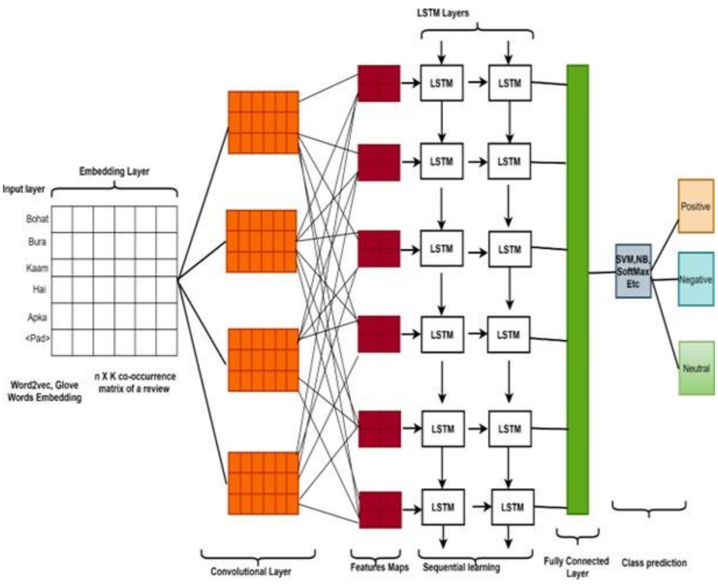

Fig 3System Architecture

Moreover, the choice of dataset and linguistic limitations, especially with German tweets, plays a role in shaping our findings. This selection highlights the nuances that can potentially impact the broader conclusions drawn from digital dialogues. Through our comprehensive approach, we intend to unravel the complexities inherent in online discourse during crisis events, shedding light on how emotions, sentiments, and solidarity dynamics manifest and transform across different stages of the crisis

- *Output Snapshots:*

Fig 4: it is the front-end execution, where user needs to login

Fig 5: user login credentials

Fig 6: uploading the dataset on which task is to be performed

Fig 7: The above preview shows the random tweets which are recorded from the twitter

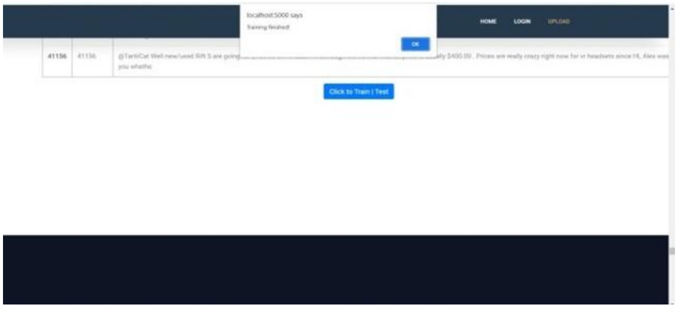

Fig 8: Initially, as it is a classification model, we need to train the model using labelled data

Fig 9: After a successful training finally, we can predict the tweet which belongs to solidarity/ant solidarity

IV. CONCLUSION

This endeavor marks a significant stride by introducing expansive human and algorithmically annotated datasets, specifically designated for delineating solidarity and its counterpoint, anti-solidarity. Leveraging the textual fabric of social media posts, our annotations discern expressions of (anti-)solidarity directed towards pertinent target groups. Notably, we attain commendable consensus among both expert and crowd annotators, despite the intricacies inherent in this pioneering NLP task. Our methodological ingenuity extends to augmented LSTM models, whose proficiency closely parallels expert agreement. Employing these models, we orchestrate an extensive trend analysis, dissecting over 270,000 social media posts before and after the COVID-19 pandemic's onset.

Within the domain of migrant solidarity discourses explicitly interwoven with COVID-19, our scrutiny unveils an abrupt surge in COVID-19 relevance as Europe implements initial measures in mid to late March 2020. This prominence swiftly ebbs, persisting at subdued levels. While scrutinizing migrant solidarity discourse with COVID-19-related keywords, (anti-)solidarity trends prove contingent on subpopulations under study. However, an intriguing pattern emerges, with all subpopulations showcasing heightened solidarity during the pandemic's early phase. An isolated focus on either phenomenon, be it migrant solidarity or anti-solidarity, can yield a deceptive portrayal of societal movement toward political orientations.

Our investigation underscores the volatility of outcomes due to multiple influencing factors, encompassing language preferences, disclosure of user location, and distinct sampling strategies, including hashtag inclusion or exclusion.

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Nonetheless, our empirical insights firmly establish that migrant solidarity experienced an amplified presence and contention during the pandemic's onset. Subsequently, its prominence dwindled, modestly falling below pre-pandemic levels by summer 2021. Noteworthy is the concurrent rise in anti-solidarity tweets within a subset of COVID-19-related posts, albeit outweighed by the prevalence of solidarity expressions.

This study serves as a clarion call for mindful research design, advocating long-term observation, judicious pre- and post-crisis comparisons, and meticulous sampling strategies. The evanescent nature of crisis-related effects necessitates such considerations. Through our comprehensive methodology and insightful findings, we contribute to the wider discourse on societal dynamics during periods of upheaval, shedding light on the complex interplay between sentiments, expressions of solidarity, and the broader socio-political landscape

V. FUTURE ENHANCEMENT

Our investigation has effectively illuminated the susceptibility of outcomes to various determinants. These encompass the language employed by users in their tweets, the disclosure or concealment of their geographic origin, and the selection of sampling strategies, whether enriched by hashtags or not. An essential lesson lies in the understanding that surges of (anti-)solidarity might not be intrinsically linked to the pandemic itself; they could potentially emerge from concurrent, interwoven political occurrences. Thus, our analysis calls for a profound delve into the data to prevent the propagation of deceptive conclusions.

While our study provides robust testament, it also beckons further exploration. We acknowledge that pronounced (anti-)solidarity instances might be intertwined with broader political narratives, necessitating a meticulous evaluation of the underlying dynamics. Our findings remain a steadfast testament that migrant solidarity underwent a discernible escalation and contestation during the pandemic's advent. Nevertheless, the prominence subsequently experienced a wane from late 2020, with tweet volume inching slightly below pre-pandemic thresholds by the summer of 2021.

Within the same timeframe, an intriguing revelation unfolded – a rise in anti-solidarity tweets within a subset of COVID-19-related posts, albeit eclipsed by the preponderance of solidarity messages. As we chart a path towards future research, these insights underscore the pivotal significance of methodological decisions. The integral role of long-term observation, meticulous pre- and post-crisis comparisons, and astute sampling strategies in crisis-focused inquiries takes center stage. As we chart a course for future enhancements, these considerations are poised to shape a comprehensive and nuanced understanding of societal dynamics during times of upheaval, steering us toward a more informed comprehension of the intricate fabric of sentiment and solidarity expressions.

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