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Analysing the Impact of Telegram (Social Media) on the Political Public Sphere: A Study on the Political Public Sphere and Deliberative Democracy

MASTER THESIS

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Abstract

This study analyses the quality of political discourse on social media by focusing on the Israel-Palestine conflict. It is based on Habermas' (2023) hypothesis, which suggests that individuals who mainly use social media platforms engage in a type of discourse that is semi-public, fragmented, and cyclical. Habermas argues that the shift from a public sphere to semi-public spheres results in what he refers to as “disrupted public spheres”. The research question of this study is: *How disrupts the telegramsphere, the political public sphere, and the deliberative discourse by sustaining and disseminating a low-quality discourse inside social media? Does the telegramsphere often spread the correspondent’s opinion-biassed discourse, and if it does, how does it accomplish this?* Thus, this study utilises a combination of quantitative machine learning analysis and Critical Discourse Analysis, employing a mixed-methods approach. The data obtained from Telegram channels was analysed in order to categorise and group recurring terms. The findings suggest that Telegram messages often exhibit a lack of high-quality discourse, characterised by emotionally charged narratives, inadequate reasoning, and a disregard for differing opinions. The goal of these research channels and topics is to strengthen group unity and spread biassed information in order to influence public opinion. In summary, the fact that Telegram is only semi-public and lacks qualitative discourse norms distorts political deliberation, which in turn undermines the diversity and quality necessary for effective deliberative democracy.

Contents

Introduction

Jürgen Habermas' recent research (2023), which analyses the *'New* Structure Transformation of the Public Sphere' and deliberative politics, serves as the motivation for this study. His theories serve as the epistemic basis for this study. He acknowledges the impact of the digitally altered communication system on the political process, underscoring the emergence of a fresh structural metamorphosis due to social media. He posits a hypothesis suggesting that individuals who primarily engage with social media platforms experience a form of communication that is semi-public, fragmented, and circular. Consequently, communication may lead to a distortion in the perception of the political public sphere. He asserts that affecting deliberative processes could potentially harm democracy (Habermas, 2023). The next section will analyse the current political landscape and its impact on the public sphere and deliberative politics.

The deliberative democracy and the public sphere

The political discourse has shifted towards virtual spaces like social media (Congge et al., 2023). These virtual spaces have the problem of favouring like-minded opinions over discordant ones, via algorithmic selection, self-selection, or both (Ross Arguedas et al., 2022). In a systematic literature study, Terren and Borge (2021) assert that the probability of opinion formation increases when there is an increase in arguments that support opinions and a decrease in information that contradicts them. However, it is notable that the problem lies not only in the fact that users engage with people who share similar interests on social media platforms, but also, and potentially more significantly, in the fact that users frequently engage in passive consumption and are exposed to content that reinforces negative attitudes (Terren & Borge-Bravo, 2021). Habermas (2023) refers to these spaces as semi-public spaces and subcultures, where people's inclination to preserve their identity constrains their perspectives. Individuals who mostly use social media to consume news demonstrate a significant decline in trust in the traditional mass media (Flew, 2021). Yet, in public communication, the mass media plays a significant role in filtering diverse opinions and providing citizens with information on topics that are relevant to society, correspondingly to the public sphere of Habermas (2023). So, the mass media actively engage in agenda setting in the public sphere, which is critical for setting topics, as demonstrated by McCombs and Shaw (1972). According to Habermas (2023), the transition from a public sphere to semi-public spheres leads to "disrupted public spheres", once disengaged from the established public sphere of journalism. Distortion arises from the decline in a political public deliberative discourse (Habermas, 2023). Thus, a progressive decline in the public sphere and deliberative politics, accompanied by the new structural transformation, the virtual space, gives rise to a semi-public sphere. Additionally, social media platforms, despite their public perception, often serve as a medium for the dissemination of disinformation (McKay & Tenove, 2021). Disinformation poses a significant threat to democracies, especially given their liberal view on media freedom (Schünemann, 2022). According to McKay and Tenove (2021), consequently, it weakens the democratic aspect by creating a feeling of widespread insincerity due to concerns about unjustified inclusion, impacting the deliberative system.

A semi-public sphere within social media; the telegramsphere

Telegram exemplifies a semi-public realm. According to Rogers (2020), Telegram has gained popularity for its messaging capabilities and its appeal to privacy-conscious users. The platform offers various communication options, group chats, and public channels, providing both privacy and exposure. Communities, including various organisations, utilise this platform due to its strong communication security measures and ability to facilitate information sharing (Rogers, 2020). Lou et al. (2021) identifies a key platform for information consumption, discussion, and news broadcasting. The term "telegramsphere" refers to the unique platform characteristics, described by Simon et al. (2023). These features include unmonitored but open channels for exchanging current affairs (Simon et al., 2023). Moreover, the sharing of information among individuals who hold similar beliefs within online communities is often unreliable (Del Vicario et al., 2016).

Concluding

This research aims to examine the dynamics of online discourse within the semi-public spaces of the Telegramsphere, by drawing upon Habermas's hypothesis and addressing social media challenges. Terren and Borge-Bravo (2021) suggest that as virtual platforms play a larger role in shaping political public conversations, there's a need for discourse analysis to understand social media's public sphere. Furthermore, this study addresses the issue of disinformation, which contradicts deliberative principles. The study seeks to address the following issues:

How disrupts the telegramsphere, the political public sphere, and the deliberative discourse by sustaining and disseminating a low-quality discourse inside social media? Does the telegramsphere often spread the correspondent's opinion-biassed discourse, and if it does, how does it accomplish this?

Theoretical Framework

Jürgen Habermas

Jürgen Habermas, born in 1929, is a German philosopher and sociologist. He is known for his research on social philosophy, including discourse, action, and rationality theory (Wikipedia contributors, 2024). In 1962, he authored the first version of 'Structural Transformation of the Public Sphere' with the support of Wolfgang Abendroth, who had both intellectual and political sway over the project (Brunkhorst et al., 2009). The 1962 publication scrutinises the 'public sphere's' development, prompting critique yet also renewing interest in broader research (Habermas, 2023). In his 'Theory of Communicative Action', he provides a framework for integrating language into the social sciences (Habermas, 1988). He expanded the concept of communicative action, incorporating it into his views on morality, democracy, and law (Fultner, 2011). In the '*New* Structural Transformation of the Public Sphere', he still focuses on the public sphere's role in maintaining the democratic community (Habermas, 2023). Habermas's concept of the public sphere has made a significant and enduring contribution to the field of social science, particularly in relation to a wider socio-structural framework (Habermas, 2023). Thereby, he acknowledges that the public sphere's social importance extends beyond shaping democratic decisions in constitutional governments (Habermas, 2023).

Public sphere

Bächtiger et al. (2018) state that deliberative democratic theorists who follow Habermas's theories see the public sphere as a domain of public existence that is apart from formal government institutions and influences public opinion. The public spheres consist of several, distinct, and interconnected entities, including political actors, social movements, and media. Additionally, it includes casual political discussions among friends, acquaintances, and internet interlocutors. Public spheres flourish when there is robust protection for political speech and association, and individuals possess a high level of ability to come together for common objectives (Bächtiger et al. 2018). However, according to Habermas (2023), the public sphere originally emerged independently from individual opinions and decisions. This is because citizens first develop their own perspective with the available information, such as social media. According to Habermas, the public sphere emerges through collaborative discourse in the form of deliberation. The quality of the discourse during deliberation determines the development of citizens' opinions in the political public sphere. Therefore, the collection and analysis of many viewpoints in the media are essential for the public sphere (Habermas, 2023). So, he defines the public sphere as a space in contemporary cultures where citizens engage in discourse about topics that are of universal importance (Brunkhorst et al., 2009). Furthermore, transnational public spheres and global civil society may operate as integral parts of a global deliberative democracy and can even act as spaces of inclusion in situations when the democratic characteristics of a state are absent (Bohman, 2007; Dryzek, 2012 in Andre Bächtiger et al., 2018).

Deliberative democracy

Deliberation politics, based on Habermas (2023), anticipates feasible solutions and provides a rationale for acceptable outcomes. Thus, democratic deliberation requires inclusive and respectful communication, considering diverse perspectives. Therefore, assumes that only the stronger argument's uncoerced power matters. Additionally, deliberation requires sense-making, involving a thorough examination of a problem before reaching a valid conclusion. These are critical prerequisites for democratic opinion-forming and decision-making processes, as well as the legitimacy of deliberative politics (Habermas, 2023).

Bächtiger and colleagues (2018), who argue in line with Habermas, defined deliberative democracy as a framework where citizens discuss political issues equally and respectfully. In these discussions, individuals assess policies impacting their lives (Bächtiger et al., 2018). Habermas' concept of deliberative politics is a theoretical framework that provides insight into a normative aspect in which democratic deliberation functions as a source of legitimacy (Floridia, 2018). Bächtiger et al. (2018) state that specific, deliberative politics primarily focuses on the perspective of political institutions and systems. On the other hand, the concept of deliberative democracy extended its influence beyond the realm of political theory, influencing both empirical research and practical endeavours (Bächtiger et al., 2018).

In the realm of deliberation and the rational-critical public, Habermas emphasises the pursuit of consensus as the ultimate objective of discussion (Andre Bächtiger et al., 2018). According to Habermas' normative foundation of deliberative politics, the influence of public discourse and the public sphere not only shapes public opinion but also serves as a means for critical examination of governmental actions (Chambers, 2018).

In the field of online deliberation, three areas of study have become prominent: non-institutional deliberation (social media and blogs), institutional deliberation (official discourse platforms between citizens and politicians), and experimental (research-focused) deliberation (Bächtiger et al., 2018 (handbook)). According to Fournier-Tombs and Di Marzo Serugendo

(2020), non-institutional discussions are more difficult to assess than the other two fields due to a variety of factors. Firstly, they adapt platforms originally created for other objectives. Secondly, they are often characterised by more openness and less strict definitions. Finally, they have a tendency to produce a much larger amount of data due to the high number of players involved (Fournier-Tombs and Di Marzo Serugendo, 2020).

Media

The process of carefully considering and developing opinions should take place in the public sphere, rather than the private sphere (Habermas, 2023). So, based on Habermas, the private sphere encompasses the personal obligations and interests that individuals within a state are both desirous of and necessary to pursue in their capacity as members of society. Conversely, the public sphere, as previously stated, refers to the domain where citizens' opinions and decisions are formulated, and where democratic decisions in the public interest for society are made (Habermas, 2023). Thus, he explicitly states the media's impact on opinion formation through the proliferation of many public perspectives among the heterogeneous community of citizens. The diverse range of opinions, filtered by the media system, allows each citizen to develop their own viewpoint and make an election choice that is as logically driven as possible from their perspective. Therefore, qualitative and independent media should maintain a focus on publicly important topics. The discourse on these topics in the public sphere forms the foundation for governmental institutions, such as the representative parliament, to acknowledge public sentiment and incorporate it into legislation (Habermas, 2023).

Discourse

Steenbergen et al. (2003) provided a comprehensive and concise outline of Habermas' ideal norms for discourse, which serve as ethical guidelines for the public sphere. They refer to all of Habermas' publications (1981, 1990, 1991, 1992, 1995, 1996) in which he discusses discourse ethics. These criteria, which are written out in brackets as follows, apply to Habermas' concept of the "ideal speech situation". However, he recognises that real political discourse often diverges considerably from the ideal framework. It should therefore be regarded as the norm for discourse, which allows the discussions to be analysed (Steenbergen et al., 2003). Firstly, they advocate for unrestricted engagement in discourse, granting every capable individual the freedom to participate (Steenbergen et al., 2003). Thus, Boswell (2013) notes the unequal connection between participants in deliberation, with few active actors and a larger passive audience. Secondly, according to Steenbergen et al. (2003) overview of Habermas discourse ethics, discourse should encompass the act of presenting sound justifications or substantiating evidence to bolster assertions, in a coherent way. Additionally, it is important for participants to consider the notion of the 'common good', encompassing attributes such as empathy, solidarity, and the general well-being of others and the community, but also self-interest. This also involves providing assistance to the disadvantaged groups in a society. It is crucial that discourse be characterised by the implementation of treating all participants with respect. One aspect of this is respect towards groups, where people recognise and accept the demands and rights of other social groups. In the dimension of respect, two other important aspects are the recognition and consideration of legitimate demands and counterarguments. These two aspects pertain to the treatment of other debate participants and play a crucial role in the deliberation process. Respecting counterarguments is crucial for considering different options, which is a vital aspect of thoughtful discussion. Discourse should aim to promote constructive politics by reaching a consensus or mutually acceptable compromise solutions, grounded in rational motivations. Lastly, in discourse, it is essential to prioritise authenticity, ensuring that verbal expressions are sincere rather than premeditated. According to Steenbergen et al. (2003), it is challenging to determine the authenticity of a speech act by assessing a person's genuine preferences versus their reported choices, since the true preferences cannot be immediately seen (Steenbergen et al., 2003).

Disinformation

McKay and Tenove (2021) conclude in their study that disinformation poses a threat to democracy by using misleading assertions as weapons to create cynicism, worsen moral degradation, and result in inauthenticity. The deliberative systems approach posits that these damages are inherent to the system and are not readily discernible via individual communication. Various players, including people, media, and elected officials, contribute to the transmission of false information and harmful behavioural norms inside the deliberative system, which in turn undermines the democratic function (McKay & Tenove, 2021).

Hochschild and Einstein (2015) underscore that the propagation of intentionally misleading false information, like the absence of authenticity in a speech act, poses a significant problem in the public sphere when political issues are involved. Disinformation, which is a specific type of misinformation, can lead to actively misinformed beliefs (Hochschild and Einstein, 2015). Guess and Lyons (2020) relate these concerns to the spread of false information masquerading as informative. These are defined as statements that distort or contradict established knowledge about observable facts (Guess and Lyons, 2020). Additionally, disinformation campaigns and foreign meddling in elections strategically manipulate public discourse with the intention of influencing it in a certain direction (Morgan, 2018 in Schünemann, 2022).

According to Flynn et al. (2017), individuals' perceptions of misperception might stem from either external factors, such as the media, or internal factors, such as prejudice. Certain misconceptions are incorrect, while others lack proof or are just unsupported. Misguided beliefs may exert influence on individuals' perspectives in the realm of politics. Nevertheless, those who hold misperceptions have a high level of confidence in their beliefs and see themselves as knowledgeable (Flynn et al., 2017). So, according to Flynn et al. (2017), misconceptions may be defined “as factual beliefs that are false or contradict the best available evidence in the public domain” (p. 128).

Willaert's (2023) research reveals that Telegram's complex and evolving narrative methods, particularly in relation to conspiracy theories and other false information, have not received adequate investigation. Narratives, which are fundamental to the organisation of discourse, are susceptible to external intervention or critical manipulation, posing a risk to public communication (Omand 2018 in Schünemann 2022). Boswell (2013) emphasises the importance of narrative for understanding deliberation based on common interests. He emphasises empirical research exploring narrative use to assess deliberative systems' authenticity and effectiveness in real-world scenarios (Boswell, 2013).

Narrative

Narratives exert an influence on interpretations of political reality, subsequently shaping our responses to or anticipations of political occurrences (Patterson and Monroe, 1998). Additionally, Boswell (2013) argues that narratives serve as instruments that individuals depend on to solidify their presumptions about political dilemmas and reach determinations on appropriate courses of action. Hence, the narratives can include certain interpretations, which are already circulating in other deliberative domains. Narratives have the ability to influence individuals' deliberative processes in ways that may be both advantageous and disadvantageous with regard to deliberative principles. This dual nature makes narrative a valuable analytical and practical instrument for evaluating deliberative systems in a broader context. The recognition of the significance of narrative in deliberative settings has important implications for the empirical analysis of deliberative democracy. They benefit from gaining a deeper grasp of narrative, since it can provide insights into the extent to which deliberative systems are really genuine in practice (Boswell, 2013).

According to Patterson and Monroe (1998), the narrative holds a major function as a fundamental instrument for comprehending human communication, particularly within the realm of discourse analysis. Thus, the discourse encompasses the collection of ideas that shape people's viewpoints, even when they remain implicit. Boswell (2013) views these phenomena as intricately linked to social interaction, often occurring on the outskirts. They impede individuals' understanding of the world, limiting the potential methods to conceptualise and debate political matters (Boswell, 2013). Thereby, language is seen, according to Marlianingsih et al. (2019), as a social activity that has an impact on persons, the subjects of discussion, and the communication techniques used. By dismantling the inherent authority in language processes, a critical discourse analysis can reveal the constraints, perspectives, and debated topics. Research demonstrates that language significantly shapes power dynamics, particularly in shaping people's perceptions and their representation in society (Marlianingsih et al., 2019). Therefore, a comment written in the form of a text, which is a product of linguistic practices, has a hidden understanding of meaning and can be used as an intermediary window to understand the relationship between discourse and the social world (Zhou and Qin, (Escobar, 2022; Filiu, 2014; Forman & Damschroder, 2007)2020 in Bakhtvar, 2022).

Research Sub-Questions

The following sub-questions (SQ) pertaining to the research question is derived from the introduction and the theoretical framework mentioned previously. So, the purpose of these sub-questions is to examine the primary research question and provide a detailed answer that aligns with the theory.

SQ1: Is the semi-public nature of the telegramsphere affected by the absence of qualitative norms for discourse?

Boswell (2013) describes how the selective character of narratives can influence the examination of influences on the diversity and relevance of deliberative discourse. Thereby, a dramatic narrative juxtaposes chaos and control, decline and renewal, and beneficial and evil (Boswell, 2013). Furthermore, the subsequent sub-questions focus on the discourse's authenticity through narrative analysis and alignment with the research question.

SQ2.1: What are the discursive characteristics of the discourse within the telegramsphere?

SQ2.2: What goals are pursued within the telegramsphere?

SQ3: How do the identified characteristics (SQ2.1) and goals (SQ2.2) of the telegramsphere influence the deliberative political discourse?

The absence of a thorough incorporation of diverse viewpoints and information-biassed opinions can be attributed to specific narratives that intentionally exclude certain perspectives and disrupt deliberative democracy. The aim of this study is to empirically examine the absence of a qualitative discussion that supports Habermas' concept of a semi-public sphere on social media platforms such as Telegram.

Method

Focus

The Israel-Palestine conflict offers an opportunity to examine discourse quality on Telegram. Individuals shape their viewpoints through social media platforms like Telegram (Kekau et al., 2023 in Escobar, 2022). The mass media's coverage of this conflict often lacks depth, leaving knowledge gaps (Johnson & Ali, 2024), or people distrust western media. Thus, shaping opinions and forming collective decisions demands qualitative discourse norms. However, it's important to note that this analysis is just one of many and can't fully encompass the entire realm of online communication. Therefore, this focus is seen as one possible approximation of a political discourse that is based on the Israel-Palestine conflict.

Brief Overview Gaza Israel Conflict

Filiu (2014) provides a detailed account of the Israeli-Palestinian conflict until 2007, including its historical timeline and causes. This complex conflict, rooted in demands for autonomy and dominance over the Jordan River and Mediterranean Sea, began when Britain took over the region after the Ottoman Empire's fall. This led to diplomatic initiatives and the UN partition resolution. Arab leaders rejected the McMahon-Hussein Correspondence and Sykes-Picot Agreement, which proposed Arab and Jewish states with Jerusalem as a special zone, resulting in violent confrontations and Israeli independence in 1948. The Nakba expelled hundreds of thousands of Palestinians after the 1948 Arab-Israeli War. In 1967, Israel seized control of the West Bank, Gaza Strip, Sinai Peninsula, and East Jerusalem, sparking Palestinian resistance. The 1978 Camp David Accords and 1993 Oslo Accords failed to address key issues, and the First and Second Intifadas intensified bloodshed. Hamas' 2006 Gaza election victory and hostilities with Israel have further complicated the situation (Filiu, 2014). On October 8th, Netanyahu declared war against Hamas following a sudden attack by Hamas militants the day before, resulting in over 1,400 Israeli deaths. Israel retaliated with extensive aerial bombardments in Gaza, leading to a reported death toll of over 10,000 Palestinians (Westfall et al., 2023).

Analysed Period

The analysis covers the period from October 7 to just after the ceasefire on December 12, 2023, chosen for significant political events influencing public discourse, starting with the Hamas attack and ending with the ceasefire. Key characteristics include a shift in sentiment from pro-Israel to pro-Palestine (Lange & Spetalnick, 2023), increased dissatisfaction from President Biden towards Prime Minister Netanyahu (Reuters, 2023), and a substantial increase in Telegram messages and diverse sentiments. This period also saw intense propaganda dissemination by official and pro-Hamas channels after the October 7 attack (McCafferty & Yilmaz, 2023). These factors make this period intriguing for analysing the development of the development of political discourse on Telegram.

Data

The Capture and Analysis Toolkit (4CAT), created by Peeters and Hagen (2022), is a versatile web-based open-source software for collecting and analysing social media data. This research uses this tool to gather messages from Telegram channels, which can have hundreds of thousands of members and are more public than private groups, making them suitable for analysis. Public chats are excluded due to a lack of moderation and constructive conversation. Telegram channels were gathered using the "searching similar channels" function with keywords like Israel, Palestine, Gaza, Israel-Palestine, and Hamas. Channels were selected based on criteria such as being English-written, mainly informative (text), official mass news media, and/or Telegram verified. Twelve channels were identified and analysed. 4CAT converted the collected data into CSV format, removing non-ASCII characters, empty rows, and comments to ensure its quality. The channels' names remain undisclosed for anonymity, but the dataset can be obtained upon request for reliability verification.

Mixed Methods Research

This research employs mixed methods research (MMR) (Escobar, 2022), integrating quantitative and qualitative approaches to answer sub-questions. The quantitative analysis is enhanced by critical discourse analysis for qualitative insights, using a parallel design to enhance intra-variability (Creswell and Plano Clark, 2011 in Escobar, 2022). The quantitative analysis addresses SQ1, while the qualitative analysis clarifies findings to answer SQ2.1 and SQ2.2. Using both methods, an analytical approach addresses SQ3. MMR aims for complementarity and expansion (Escobar, 2022). The methods section first operationalizes the quantitative analysis, followed by qualitative illustrations to complement and enhance reliability.

Quantitative Method

The Discourse Quality Index

This study uses the Discourse Quality Index (DQI) to quantitatively analyse the quality of discourse on Telegram, focusing on Habermas' ideal speech norms. The DQI is a recognised methodology for implementing Habermas's debate criteria (Ercan et al., 2022 in Steenbergen et al., 2003). It measures and quantifies discourse quality by assessing how messages deviate from ideal norms (Steenbergen et al., 2003). This entails manually coding components identified by Steenbergen et al. (2003), including participation degree, justification level, content of justifications, respect, counterarguments, and emphasis on constructive politics. Quantifying these norms with the DQI enables the evaluation of whether Telegram discourse quality is diminished due to the absence of qualitative norms. The coding scheme is provided in Table 1.

Table 1: DQI coding scheme

Participation	Coded as 0 when there is no option to comment, and as 1 when there is a link provided to comment on the message.
Justification Levels	0 for no justification (X should or should not be done without a reason), 1 for inferior justification (provides a reason for Y but no linkage between X and Y), 2 for qualified justification (links X to or detracts from Y), and 3 for sophisticated justification (two complete justifications for the same demand).
Content of Justifications	Coded as 0 for explicit statements about group interests, 1 for neutral statements, and 2 for utilitarian terms, including explicit articulation of the common good in relation to the difference principle.
Respect	Measured using codes 0 for negative statements, 1 for non-explicit positive statements, and 2 for at least one explicitly positive statement about groups.
Counterarguments	Evaluated as a summary judgement of respect, with codes 0 for ignored, 1 for included but degraded, 2 for acknowledged, and 3 for included and valued.

Constructive Politics	0 maintain their positions without compromise, 1 for alternative proposals, and 2 by presenting a conciliatory suggestion that is suitable for the current schedule.

DelibAnalysis

To address SQ1, this research uses a supervised machine learning framework to quantitatively analyse Telegram discourse. Due to the vast number of messages, manual DQI coding is impractical. The study uses DelibAnalysis, executed with Python, as detailed in the code available on GitHub by Fournier-Tombs and Di Marzo Serugendo (2018), included in Appendix 5. According to the DQI, DelibAnalysis quantitatively assesses Telegram messages. Steps include manually labelling a small random data sample, training and validating a classifier, applying it to unlabelled data, creating topic clusters, and interpreting results. These insights determine the extent of low-quality discourse on Telegram and how it diverges from ideal norms. Identified patterns guide qualitative research, which addresses SQ2 by illustrating trends and themes' impact on discourse quality. This ensures qualitative analysis is based on quantitative findings, providing a comprehensive understanding of Telegram's influence on political discourse around the Israel-Palestine conflict.

Machine training and learning

Machine learning, as noted by Fournier-Tombs (2018), is increasingly used in social science for content analysis, including discourse analysis, to automate large dataset analyses. The model quantifies text elements, like syntactic or semantic features, for machine learning computations, enabling automatic comment categorization based on a labelled dataset and improving Telegram message analysis efficiency and efficacy.

A key part involves manually labelling the DQI scores 0-14 points into a random subset of the data. These scores are categorized as low 0-5, medium 6-10, and high 11-14 quality discourse. After that, the labelled dataset is split into training (80%) and testing (20%) sets, as done by Fournier-Tombs (2018). The training set fits a Random Forest[1] model and is tested with the remaining data. The goal is to achieve a minimum F1 score of 80% using a Support Vector Machine[2] (SVM) classifier, ensuring model reliability and validity (see Appendix 2).

[1] Random Forest is a machine learning algorithm that use ensemble learning to predict features based on a random subset of data.
[2] Support Vector Machine is a classifier algorithm that creates an optimal separation, assigning non-labelled data to each side based on weight/feature combinations.

Model Classification

The F1 score measures a model's accuracy in binary classification, being the harmonic mean of precision and recall, with values ranging from 0 (worst) to 1 (best). It is calculated as:

$$F1 = 2 \times \frac{precision \times recall}{recision + recall}$$

Precision is defined as the ratio of true positive results to all positive results, whereas recall captures all true positive cases. The weighted average F1 score accounts for class imbalances by considering the proportion of instances in each class. This metric is particularly useful in evaluating classification models with imbalanced datasets (Scikit-learn, n.d.).

The performance report (Appendix 2) evaluates the model on a test set of 44 observations against 173 in the training data. The model shows a precision of 0.95 and a recall of 1.00 for class 0, indicating strong performance. For class 1, precision is 1.00, but recall is 0.33, indicating low recall. The overall accuracy is 0.95, with a macro average F1-score of 0.74 and a weighted average F1-score of 0.94. Class 2 is missing due to insufficient training data, and the limited number and low recall of Class 1 restrict the model's predictive scope. These limitations will be addressed in the subsequent discussion.

Clustering Frequent Terms

DelibAnalysis uses clustering to quantify dominant narratives within the discourse, as well as assess potential perspective restrictions. Both discussion quality and narrative diversity are crucial in a deliberative democracy. Subjects are classified into thematic clusters based on significance and frequency. Topic modelling, using a k-means[3] clustering algorithm (Scikit-learn developers, 2007-2024), groups the top 15 3-gram terms from comments into distinct clusters. Data is vectorized with Term Frequency-Inverse Document Frequency (TF-IDF) to analyse term frequency and importance. This process identifies significant three-word phrases, with larger clusters indicating common themes and smaller clusters containing niche information. Within clusters, comment counts indicate data concentration. These clustering results describe the discursive characteristics (SQ2.1) and goals (SQ2.2) of the Israel-Palestine discourse. The qualitative analysis will then illustrate these findings, providing a deeper understanding of how these characteristics and goals influence deliberative political discourse.

[3] k-means clustering is an approach used to group n observations into k groups based on their similarity to the mean value of each cluster.

Qualitative Method

Critical Discourse Analysis

The goal of this qualitative research is to illustrate phenomena rather than draw broad statistical conclusions (Forman & Damschroder, 2007). Fairclough's Critical Discourse Analysis (CDA), as summarised by Janks (1997), involves three interconnected processes: textual analysis, processing analysis, and social analysis (Figure 1). Textual analysis examines verbal processes and describes the text, probing the interconnection between clauses and phrases (Janks, 1997). Messages will be analysed by using Halliday's transitivity analysis (as cited in Janks, 1997) to describe the rhetorical mode, including argumentation and narrative (Fairclough, 1992). Processing analysis tries to figure out how discourse is produced by interpreting spoken language and the content of discourse (Box 2 in Figure 1 of Janks, 1997). Sociocultural practices embed both message and discourse, offering a comprehensive explanation. Social analysis examines production conditions and environmental interpretation (Box 1 in Figure 1 of Janks, 1997). Fairclough's CDA framework integrates an analytical approach, highlighting interdependent explanatory capabilities to demonstrate the quantitatively assessed quality of discourse.

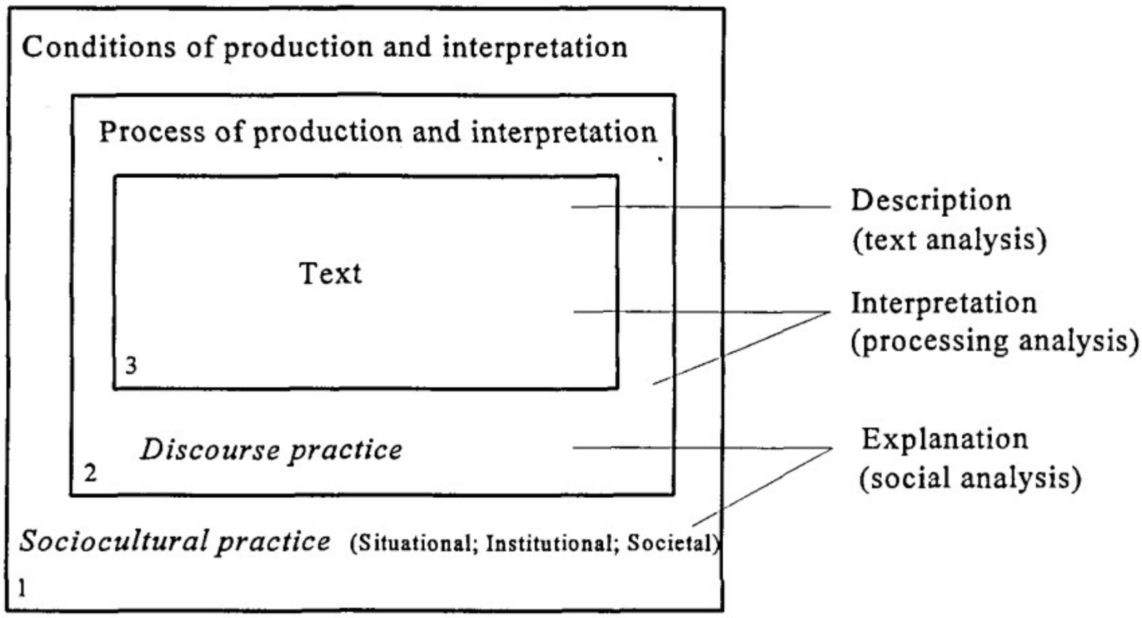

Figure 1 Fairclough's dimension of discourse and discourse analysis (Adapted from Janks, 1997)

CDA uncovers how Telegram messages use language to construct meaning and reflect power dynamics and ideologies. This analysis considers the characteristics (SQ2.1) and goals

(SQ2.2) of the discourse, shedding light on quantitative findings. Based on Halliday's transitivity analysis, textual analysis (Box 1) looks at visual clues, the discourse quality index, and verbal processes, with a focus on material, mental, relational, behavioural, and existential processes. Discourse practice (Box 2) determines the message's purpose and narrative style. Sociocultural practice (Box 1) examines power dynamics, marginalisation, and ideologies in the discourse. Appendix 6 contains the more comprehensive and utilised analysis template for this research.

Messages are selected based on clusters and frequent terms from quantitative analysis, focusing on those twice the average length of the channel for extensive content. Searches will target one of the five most frequently mentioned terms, and the message with the highest views will be included if multiple are available. Additionally, two messages will be selected from the top four channels with the highest average views for a comprehensive viewpoint. In total, 16 messages will be analysed with CDA.

Results

Quantitative Analysis

Channels Reach

The original dataset consisted of 48,640 messages, but after undergoing the cleaning process, 38,843 messages remain for analysis. The channel with the highest number of views has an average of 115,000 views per comment, while the second-highest channel has 100,000 views. The remaining channels have an average viewership of 1,500 to 20,000 views per comment. One of the highest-viewed channels generates the highest number of comments per day, with an average of 150 comments. Four other channels show significant commenting activity, with comment volumes ranging from 50 to 150. The peak comment volume occurs within the initial eight days of the period, and the average number of charts per comment per channel falls between 123 and 667. The distribution of charts per comment is generally consistent across channels, except for one channel with significantly lower average comments and views but the highest average number of charts.

DQI Analysis

The mean of 0.0138 for the DQI across all the Telegram messages in the dataset illustrates that most of the messages have low quality. The DQI scores appear to cluster around the mean value, as indicated by the small standard deviation of 0.1172. A skewness value of 8.4221 indicates a significantly positive skewness, suggesting that the majority of messages have a low DQI score, while a smaller number of messages have a medium or high DQI score. The kurtosis value of 70.0108 suggests messages with exceptionally low DQI scores. The high skewness and kurtosis values indicate a scarcity of discourse messages of superior quality.

The graph in Appendix 4 illustrates the probability of assigning a specific category to a comment: 98.62% of messages receive a DQI score of 0, signifying low discourse quality. A small percentage of 1.37% receive a medium quality score of 1, and a very small number of 0.0052% of messages are assigned a high quality score of 2. Therefore, it is important to approach the last one with care, as the model's classification was trained with a small, practically non-existent sample for the particular DQI score.

Frequency of Cluster and Terms

Table 2 displays the top 15 3-gram terms for each of the 5 clusters. Cluster 1 is the most discussed, while the other four clusters are at similar levels (Appendix 3). The silhouette coefficient, ranging from -1 to 1, quantifies an object's similarity to its own cluster relative to others. The optimal number of clusters was determined to be five with a silhouette value of 0.333, which indicates a moderate level of similarity, showing moderate cohesion and distinctness among clusters. The overall dataset's most frequent terms are “campaign”, “children”, “far”, “offensive”, and “actions” suggest a pattern of discourse centred on a sovereignty of interpretation.

Table 2: The top 15 3-grams terms in each cluster

Cluster	Terms
0	sy martyr izz; response zionist massacres; qassam brigades target; brigades al qassam; qassam brigades al; qassam brigades bombard; aal qassam brigades; brigades aal qassam; qassam brigades aal; martyr izz el; el din al; izz el din; din al qassam; al aqsa flood; al qassam brigades
1	since beginning war; palestinian resistance gaza; camp central gaza; gaza https qudsnen; south gaza strip; palestinian ministry health; north gaza strip; occupied west bank; https bit ly; al shifa hospital; northern gaza strip; israeli occupation forces; missile sirens ring; al aqsa flood; comment follow link
2	pm saraya al; al quds asaraya; quds asaraya al; quds aas part; asaraya al quds; al quds bombard; quds jenin brigade; al quds jenin; al quds awe; aas part al; part al aqsa; aqsa flood battle; asi saraya al; saraya al quds; al aqsa flood

3	sirens sounded lakhish; sirens sounded central; sounded city ashkelon; area details follow; sirens sounded kibbutz; sirens sounded city; strip details follow; gaza strip details; sounded area surrounding; sirens sounded area; area surrounding gaza; surrounding gaza strip; report sirens sounded; initial report sirens; idf initial report
4	war comment follow; israelto comment follow; today comment follow; hospital comment follow; territory comment follow; area comment follow; ministry foreign affairs; senior hamas official; since beginning war; short time ago; anti tank missiles; palestinian ministry health; north gaza strip; northern gaza strip; comment follow link

Interpretation

These most commonly used 3-word phrases (Table 2) reveal patterns in the discourse on Telegram channels regarding the Israel-Palestine conflict and provide an understanding of frequent discursive topics. The most discussed phrases, as seen in Cluster 1, indicate that the narrative characterises the discourse as one deeply concerned with persistent violence and occupation. For instance, with terms like “since beginning war”, “Palestinian resistance Gaza”, “Al Shifa Hospital”, “occupied West Bank”, and “Israeli occupation forces”. The phrase “Al-Aqsa Flood”, mentioned by militant organisations, refers to the attack on Israel that took place on October 7th. It seems that this term does not convey a neutral perspective on the event. Other terms emphasize the significance of distinct regions. Shown are frequently mentioned locations like the “central Gaza camp” and various regions across the “Gaza Strip”, such as the “south”, “north”, and “northern” areas. It centres on regions, which could be seen as an informative indication. As well, the “Missile sirens ringing” could be seen as an informative service. The term "https" indicates that additional information is shared from alternative sources. Cluster 1 involves actively disseminating information while also allowing patterns of interpretation, which has the potential to influence how the conflict is perceived internationally.

Clusters 0, 2, 3, and 4, while less frequent, bring attention to various aspects of the conflict. There is a strong emphasis on militant activities and commemorations, with terms like “Al-Qassam Brigades” and “response zionist massacres”, highlighting narratives of resistance and retaliation. Phrases like “Sirens sounded central” also focus on alerts and defensive responses to threats. In addition, providing the possibility to “comment” allows for a potential means of participating in the discussion. Overall, these patterns suggest that the telegramsphere sustains and disseminates discourse characterised by themes of resistance, defence, ongoing conflict, and active engagement, potentially reinforcing specific viewpoints and biases within the conflict.

Qualitative Analysis

Critical Discourse Analysis

Most messages use the active voice, emphasising actions and agency, as seen in phrases like “Will support Israel” or “Are all slander campaigns”. Whereas passive voice, used less frequently, focuses on outcomes, such as “Aid trucks carrying humanitarian aid and fuel entered Gaza”. Furthermore, material processes dominate, with terms like “vowed to keep fighting” and “IDF thwarted terrorists” emphasising aggressive narratives. Mental processes, such as “the world has watched in horror”, propose collective perceptions, while relational processes like “the terrorist actions of Hamas have no justification” try to establish clear states of being.

The purpose of the discourse becomes evident through the use of the discourse practice of the CDA. On one side, the authors aim to justify military actions as necessary and defensive, while others mention their operational success and security. The narrative styles vary, with some using a narrative to justify violence and others mobilising or adopting an authoritative tone. But many messages lack coherent justification and prioritise group interests over the common good, with assertions without substantial arguments. For instance, terms like “genocide campaign” or “Politicians can make whatever promises they like - but the evidence is there for all to see” do not consistently and directly substantiate their claims. These messages aim more to reinforce group identity and vilify opposition, using emotionally charged language and selective presentation of facts. Counterarguments are often dismissed, neglecting alternative viewpoints, with authors criticising activities of one conflict side and overlooking possible reasons for these actions, and vice versa. Disagreement prevails, with little attempt to compromise, exemplified by assertions like “We cannot back a party that refuses to demand a halt in fighting”.

The power dynamics, by examining the sociocultural practice, are explicit with statements showcasing military control and strength, while others highlight resistance against oppression. Marginalisation is a key theme that emphasises civilian suffering to garner international sympathy. Promoted ideologies range from resistance and the legitimacy of armed struggle to security and national defence. For example, authors portray the opposite side as systematic and aggressive, while these sides try to justify their military actions as defensive. Dramatic narratives, such as portraying children as victims and framing military actions as necessary for national security, align with Boswell's (2013) description of dramatic narratives. The selective nature of these narratives and the repetition of specific opinions without incorporating diverse viewpoints suggest a lack of authenticity. This lack of diversity and relevance indicates that the telegramsphere's discourse lacks the authenticity necessary for authentic deliberation. Overall, the CDA reveals biassed narratives, reinforcing group identity and vilifying opposition through emotionally charged, mostly active voice language and selective facts, ultimately highlighting a lack of constructive discourse.

Conclusion of Quantitative Analysis with Qualitative Illustration

SQ1: Is the semi-public nature of the telegramsphere affected by the absence of qualitative norms for discourse?

The discourse on Telegram regarding the Israel-Palestine topic is greatly influenced by a lack of quality discourse norms. This causes a distortion of political public deliberative discourse, which hinders the flourishing of public spheres (Bächtiger et al., 2018). Thereby, it hinders the deliberative process that determines the opinions of citizens and may harm democracy (Habermas, 2023). Additionally, the nature of the telegramsphere doesn't contribute to fulfilling a role as a media for critically analysing government actions or as a reliable and unbiased source of media, as described by Chambers (2018) and Habermas (2023). Because the model's accuracy for classes 1 and 2 is low, it is important to interpret the results cautiously. However, the illustration with the qualitative CDA indicates a similar trend.

SQ2.1: What are the discursive characteristics of the discourse within the telegramsphere?

Messages frequently lack thorough justification, use emotionally charged narratives, display low respect for opposing viewpoints, and fail to provide new input or counterarguments. The messages predominantly use an active voice and use authoritative and mobilising tones, which are dominated by material processes. Furthermore, there is a lack of genuine effort to compromise and a lack of authentic perspectives. This leads to a fragmented and circular discourse that reinforces like-minded opinions and negative attitudes, lacking the diversity necessary for effective deliberation (Boswell, 2013; Patterson & Monroe, 1998; Ross Arguedas et al., 2022; Terren & Borge-Bravo, 2021). These discursive characteristics, in addition to the high viewership of certain channels, could have a significant impact on politically engaged users globally, shaping their perceptions in a way that undermines the diversity and quality necessary for effective deliberation (Bohman 2007; Dryzek 2012 in Andre Bächtiger et al., 2018; Habermas, 2023).

SQ2.2: ***What goals are pursued within the telegramsphere?***

Within the realm of Telegram, the main objectives of the researched channels are to strengthen group identity, advocate for particular political agendas, and spread prejudiced information to influence public opinion. These Telegram channels aim to unify people who share similar beliefs by promoting emotionally charged and biased narratives that lack comprehensive justification. This approach enhances the unity and solidarity within a particular group while disregarding or excluding opposing perspectives (Boswell, 2013). Moreover, numerous channels may exhibit a propensity to propagate false information and manipulate public discussions in order to promote their own ideological viewpoints, thereby exerting influence on political participation and shaping public opinion to favour their particular agendas (McKay & Tenove, 2021; Boswell, 2013). The objective of prioritising narrative control and selective information distribution may be to undermine the credibility of opposing viewpoints and maintain an authority dominant discourse on the platform (Guess and Lyons, 2020; Marlianingsih et al., 2019; Omand, 2018 in Schünemann, 2022).

SQ3: How do the identified characteristics (SQ2.1) and goals (SQ2.2) of the telegramsphere influence the deliberative political discourse?

Influence on the Political Public Sphere

The characteristics of the telegramsphere can create echo chambers, exposing readers mainly to information aligning with their pre-existing beliefs, reinforcing ideological divides, and reducing consensus-building (Boswell, 2013). This selective exposure limits diverse interactions, fostering a polarised public sphere, which is detrimental to deliberative democracy (Habermas, 2023). Emotionally charged and biassed narratives on Telegram manipulate public perception, shifting the focus from informed debate to sensationalism (Omand, 2018 in Schünemann, 2022). While Telegram could supplement independent media with comprehensive coverage, it often hinders political deliberations by focusing on minor or irrelevant topics, fostering a lack of knowledge for the public sphere (Habermas, 2023). This leads to this semi-public sphere, which Habermas (2023) describes with the “New Structure Transformation of the Public Sphere” hypotheses.

Influence on the deliberative political discourse

This semi-public sphere lacks a clear objective to seek agreement or find common ground. The content is unauthentic and could include misconceptions or misleading information, leading to potential bias (Boswell, 2013; Hochschild & Einstein, 2015; McKay & Tenove, 2021; Steenbergen et al., 2003). Fragmented and circular discourse reinforces like-minded opinions, undermining rational debate essential for deliberative politics (Ross Arguedas et al., 2022; Terren & Borge-Bravo, 2021; Habermas, 2023). Exclusionary practices and biassed narratives within the telegramsphere limit political deliberation, diminishing democratic legitimacy (Flynn et al., 2017). Dramatic narratives, such as depicting children as victims and presenting military actions as essential for national security or frequently mentioning the term offensive, align with Boswell's (2013) characterization of dramatic narratives. These narratives pose a danger to public communication and are susceptible to manipulation. In addition, there is a lack of quality in the discourse for a balanced exchange. In summary, the telegramsphere influences deliberative political discourse by reinforcing biases, promoting polarised narratives, and undermining rational debate, eroding the quality of the political public sphere and deliberative democracy.

Discussion

This study offers insights into the deliberative dynamics of online discourse within the telegramsphere, illustrating how its low quality and its characteristics and goals weaken the political public sphere. The concern of Habermas (2023) about social media as a semi-public sphere can be seen in the telegramsphere. The tendency to generate emotionally charged narratives creates echo chambers. This refers to the deliberate dissemination of unauthentic information, including disinformation, that supports specific ideologies, thereby reducing exposure to diverse perspectives. The deliberation and political public sphere necessitate the ability to comprehend and evaluate (counter)arguments, enabling one to understand the perspective of the opposing party and act in solidarity. This cannot be achieved in the telegramsphere, with its low level of qualitative discourse norms. Furthermore, the telegramsphere is unable to enhance transnational public spheres and global civil society. It lacks the fundamental components and relevant societal topics to be discussed in the discourse required to achieve a deliberative democracy (Bohman 2007; Dryzek 2012 in Andre Bächtiger et al., 2018). Therefore, the chosen topic of research on Telegram weakens the development of an informed political public sphere and deliberative discourse, along with their mentioned characteristics.

Strengths

One strength of the research is the insights gained from qualitative and quantitative methods by adopting Escobar's (2022) MMR framework. The main advantage lies in its comprehensive analysis of both the discourse's quality and narratives. This improves the reliability of the quantitative findings. Additionally, this study uses an interdisciplinary approach for a valid understanding of the quality of discourse in a social media environment. It integrates communication studies, data science, psychology, and political science. Communication science explains discourse construction and dissemination with the use of the CDA and the importance of media. Thereby, it relays psychological approaches to explain group dynamics and people's perceptions of narratives. Data science methods, along with their machine learning tools, are used to effectively analyse large datasets and identify patterns. Political science offers comprehensive socio-political theory and interpretation throughout the research issue.

Limitations

The dataset comprises all publicly accessible Telegram channels that meet the specified selection criteria. Thereby, it’s significantly imbalanced, with a prevalence of lower-quality discourse examples, which was recognised in the manual coded data. This implies that the model receives insufficient training from middle-quality examples and no training at all from high-quality examples. In addition, the focus is on Telegram on only one topic, disregarding other social media platforms. This limitation affects the research question, which seeks to understand Telegram's broader impact on the political public sphere and deliberative discourse. Focusing solely on the Israel-Palestine discussion on Telegram may lead to an incomplete understanding of how the platform facilitates and disseminates substandard discourse. Additionally, the absence of comparative analysis across different platforms hinders our comprehension of how Telegram specifically promotes biassed discourse. Also, it remains uncertain whether other social media platforms distort the public sphere. The limited sample size that is used for the CDA primarily illustrates the findings and does not represent the entire dataset. A broader overview is achieved through the analysis of 3-gram clusters and frequently occurring terms. However, interpretations rely on the researcher and may be subject to bias. Potential discrepancies in comment labelling should be considered, as the dataset was labelled by the researcher. The qualitative CDA involves subjective data interpretation, consistent with the underlying theory, but this subjectivity can also be seen as a limitation.

Context and Recommendations

According to Willaert (2023), Telegram channels frequently spread various narratives, some prejudiced, especially within conspiracy theories and far-right counterculture channels. Interpreting these findings with the outcomes of this study aligns with recent research on the impact of social media on deliberative democracy (Willaert, 2023). As a result, research emphasizes the need for strong content moderation and digital literacy programs to improve online conversations and reduce the negative effects of biased discussions on democratic participation. To enhance the quality of online discussions, it is necessary to improve content moderation and promote greater digital literacy (Bächtiger et al., 2018; Chambers, 2018; Dryzek et al., 2019; Fournier-Tombs & Di Marzo Serugendo, 2020; McKay & Tenove, 2021; Schiffrin, 2017). In summary, this study offers insights into the deliberative democracy of online discourse within the telegramsphere, illustrating how the low quality and dramatic charged nature of the content, driven by specific ideological goals, weaken the political public sphere.

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Appendix

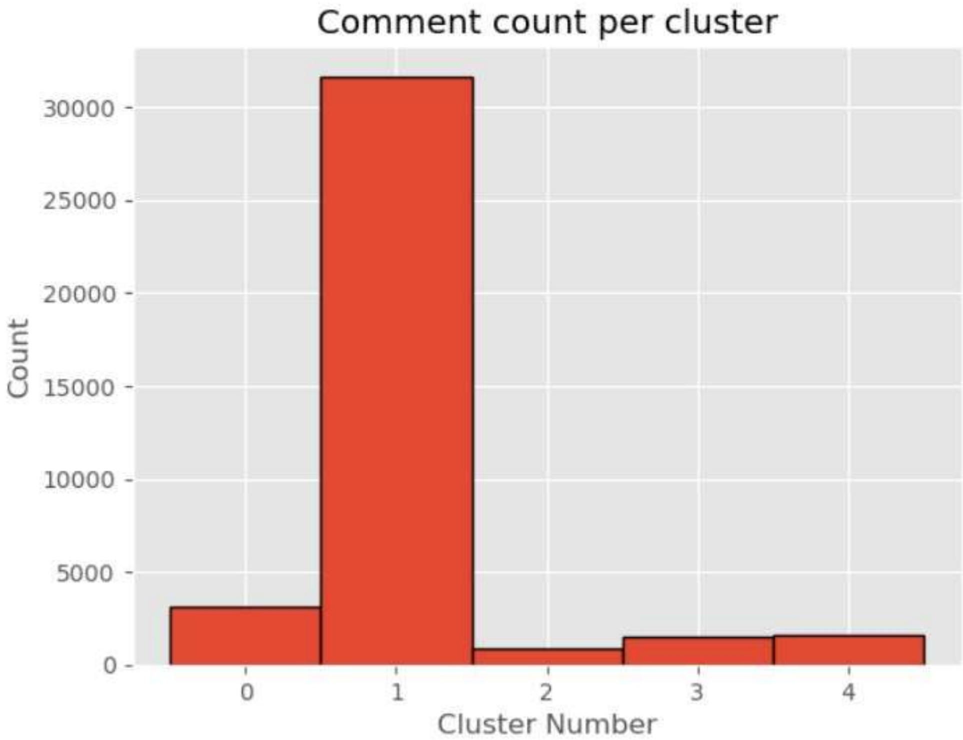
Appendix 1

Participation	Coded as 0 when there is no option to comment, and as 1 when there is a link provided to comment on the message.
Justification Levels	0 for no justification (X should or should not be done without a reason), 1 for inferior justification (provides a reason for Y but no linkage between X and Y), 2 for qualified justification (links X to or detracts from Y), and 3 for sophisticated justification (two complete justifications for the same demand).
Content of Justifications	Coded as 0 for explicit statements about group interests, 1 for neutral statements, and 2 for utilitarian terms, including explicit articulation of the common good in relation to the difference principle.
Respect	Measured using codes 0 for negative statements, 1 for non-explicit positive statements, and 2 for at least one explicitly positive statement about groups.
Counterarguments	Evaluated as a summary judgement of respect, with codes 0 for ignored, 1 for included but degraded, 2 for acknowledged, and 3 for included and valued.
Constructive Politics	0 maintain their positions without compromise, 1 for alternative proposals, and 2 by presenting a conciliatory suggestion that is suitable for the current schedule.

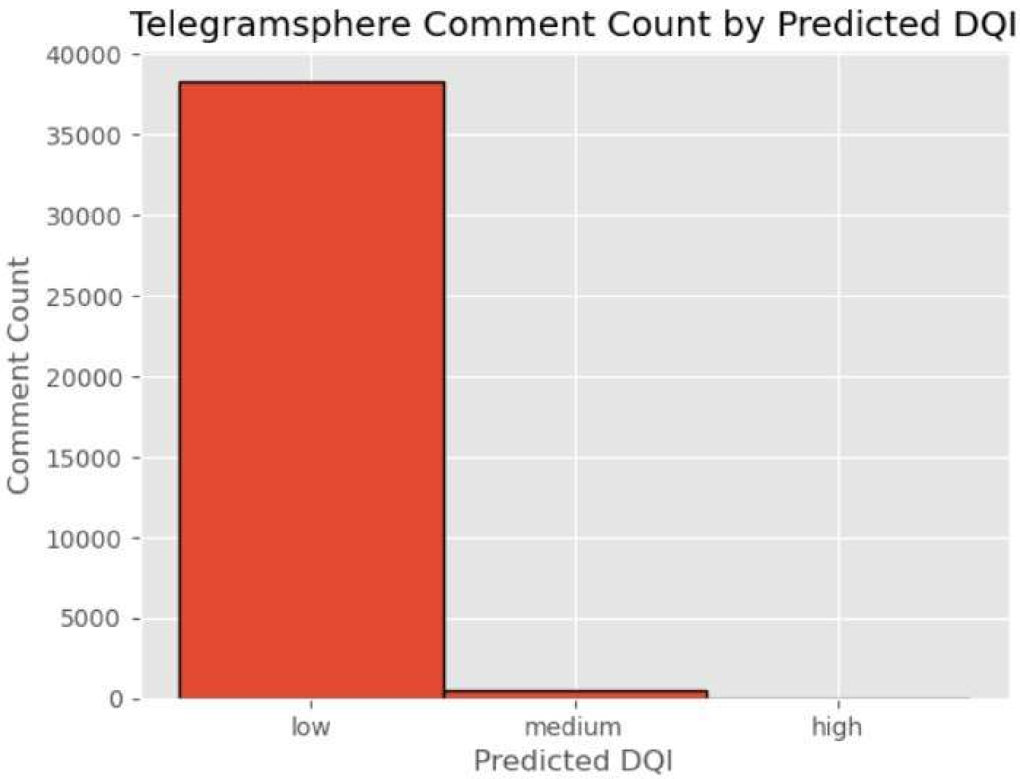
Appendix 2

Metric	Precision	Recall	F1-Score	Support
0	0.95	1.00	0.98	41
1	1.00	0.33	0.50	3
Accuracy	-	-	0.95	44
Macro Avg	0.98	0.67	0.74	44
Weighted Avg	0.96	0.95	0.94	44

Appendix 3



Appendix 4



Appendix 5

```python
from sklearn.metrics import classification_report
from sklearn.ensemble import RandomForestClassifier
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.model_selection import train_test_split
from sklearn.utils.class_weight import compute_class_weight
import nltk
import re
from nltk.corpus import stopwords
import pandas as pd
import numpy as np
%matplotlib inline
import matplotlib.pyplot as plt
plt.style.use('ggplot')
```

```python
def process_labelled_data(source_csv):
    data_df = pd.read_csv(source_csv)
    data_df = data_df.dropna(subset=['comment'])  # Nur Zeilen entfernen, in denen 'comment' NA ist
    indicators = ['participation', 'level_of_justification', 'content_of_justification', 'respect', 'counterarguments', 'constructive_politics']
    data_df['dqi'] = data_df[indicators].sum(axis=1)
    data_df['dqi_groups'] = data_df.dqi.map( lambda x: 0 if x <= 5 else 1 if (x > 5 and x <=10) else 2)
    data = data_df[['comment', 'dqi', 'dqi_groups']]
    return data

def comment_to_words(raw_comment):
    try:
        letters_only = re.sub("[^a-zA-Z]", " ", raw_comment)
        words = letters_only.lower().split()
        stops = set (stopwords.words ("english"))
        meaningful_words = [w for w in words if not w in stops]
        return(" ".join(meaningful_words))
    except TypeError:
        print(raw_comment)

def append_features(input_matrix, input_feature):
    count = 0
    new_matrix = np.zeros(shape=(input_matrix.shape[0], input_matrix.shape[1]+1))
    for i in range(0, len(input_feature)):
        if isinstance(input_feature[i], str):
            # Handle string values
            new_matrix[i] = np.append(input_matrix[i], 0.0)  # Replace with a default float value
        else:
            new_matrix[i] = np.append(input_matrix[i], input_feature[i])
    return new_matrix

char_dict = {'less_than_30_chars': (30,0), 'between_30_and_100_chars': (100,30),
             'between_100_and_300_chars': (300, 100), 'between_300_and_800_chars': (800, 300),
             'between_800_and_1500_chars': (1500, 800), 'between_1500_and_3000_chars': (3000, 1500), 'more_than_3000_chars': (1000000, 3000)}

def add_character_counts(data, chars):
    data['comment'] = data['comment'].astype(str)
    data['char_count'] = data['comment'].apply(lambda x: len(x))
    for k, v in chars.items():
        data[k] = data.char_count.map(lambda x: 1 if (x <= v[0] and x > v[1]) else 0)
    return data
```

```python
labelled_data = process_labelled_data("C:\\Users\\LabUser\\Desktop\\DataFolder\\TrainingData_Set\\stored\\clean_labelled3.csv")
labelled_data["cleaned_comment"] = labelled_data["comment"].apply(lambda x: comment_to_words(x))
labelled_data = add_character_counts(labelled_data, char_dict)
print(labelled_data.head())
```

```python
# Train classifier

train, test = train_test_split(labelled_data, train_size = 0.8, random_state = 44)

vectorizer = CountVectorizer(analyzer = "word", tokenizer = None, preprocessor = None, stop_words = None, \
                             max_features = 6000)

train_data_features = vectorizer.fit_transform(train["cleaned_comment"])
train_data_features = train_data_features.toarray()

print(train_data_features.shape)


quantitative_features = ["less_than_30_chars", "between_30_and_100_chars",
                         "between_100_and_300_chars", "between_300_and_800_chars",
                         "between_800_and_1500_chars", "between_1500_and_3000_chars", "more_than_3000_chars"]
for i in quantitative_features:
    train_data_features = append_features(train_data_features, train[i].to_numpy())

print('Number of comments, number of features')
print(train_data_features.shape)
```

```
# Create the classifier (normal)

# Compute class weights
#classes = np.unique(train['dqi_groups'])


# Create a dictionary mapping class labels to their weights


forest = RandomForestClassifier(n_jobs=-1, n_estimators=24, criterion="entropy", max_depth=17, warm_start=True,
                               max_features= 3000, bootstrap=True)


y,_ = pd.factorize(train['dqi_groups'])
forest.fit(train_data_features, y)


# View the top features used by the classifier by importance

importances = forest.feature_importances_
std = np.std([tree.feature_importances_ for tree in forest.estimators_],
             axis=0)
indices = np.argsort(importances)[::-1]
vocab = vectorizer.get_feature_names_out().tolist() #new
#feature_names = [feature for feature, index in sorted(vectorizer.vocabulary_.items(), key=lambda item: item[1])]
for i in quantitative_features:
    vocab.append(i) #new
    #feature_names.append(i)

# Print the feature ranking
print("Feature ranking:")

feature_importance_df = pd.DataFrame(data=None, columns = ['Feature name', 'Importance'])
for f in range(0,70):
    feature_importance_df.loc[f+1] = [vocab[indices[f]], importances[indices[f]]] #new
    #feature_importance_df.loc[f+1] = [feature_names[indices[f]], importances[indices[f]]]

plt = feature_importance_df.plot(kind="barh", figsize=(15,15), color="purple")
plt.set_yticklabels(feature_importance_df["Feature name"])
plt.invert_yaxis()
plt.set_title("Top 70 features by importance")
plt.set_xlabel("Importance")
plt.set_ylabel("Feature name")


#Feature ranking: output

test_data_features = vectorizer.transform(test["cleaned_comment"])
test_data_features = test_data_features.toarray()

print(test_data_features.shape)

for i in quantitative_features:
    test_data_features = append_features(test_data_features, test[i].to_numpy())

print('Number of comments, number of features')
print(test_data_features.shape)

#Evaluate the classifier by predicting the score of the test group

result = forest.predict(test_data_features)

output = pd.DataFrame(data={"actual_dqi": test["dqi_groups"], "predicted_dqi": result})

# Create confusion matrix

print(pd.crosstab(output['actual_dqi'], output['predicted_dqi'], rownames=['Actual'], \
                  colnames=['Predicted']))

print ('\n*Classification Report:\n', classification_report(output['actual_dqi'], output['predicted_dqi']))


def process_unlabelled_data(source_csv):
    data_df = pd.read_csv(source_csv)
    data_df = data_df.dropna(subset=['comment'])  # Remove rows where 'comment' is NA
    data = data_df[['comment']]
    return data

# Load and preprocess unlabelled data
unlabelled_data = process_unlabelled_data("C:\\Users\\LabUser\\Desktop\\DataFolder\\TrainingData_Set\\stored\\unlabelled2.csv")
unlabelled_data["cleaned_comment"] = unlabelled_data["comment"].apply(lambda x: comment_to_words(x))
unlabelled_data = add_character_counts(unlabelled_data, char_dict)

# Transform unlabelled data features
unlabelled_data_features = vectorizer.transform(unlabelled_data["cleaned_comment"])
unlabelled_data_features = unlabelled_data_features.toarray()

# Append features
for i in quantitative_features:
    unlabelled_data_features = append_features(unlabelled_data_features, unlabelled_data[i].to_numpy())

# Predict the score of the unlabelled data
result = forest.predict(unlabelled_data_features)

# Output the predicted scores
output = pd.DataFrame(data={"predicted_dqi": result})
print(output.head())
```

```
#Plot the comment count by predicted DQI

plt = output.hist('predicted_dqi',color="cornflowerblue")
plt[0][0].set_xlabel("Predicted DQI")
plt[0][0].set_ylabel("Count")
plt[0][0].set_title("tele Discussion: Comment Count by Predicted DQI")
print('\n')
print('Mean', output['predicted_dqi'].mean())
print('Minimum', output['predicted_dqi'].min())
print('Maximum', output['predicted_dqi'].max())
print('Standard Deviation', output['predicted_dqi'].std())
print('Skew', output['predicted_dqi'].skew())
print( 'Kurtosis', output['predicted_dqi'].kurt())
print('\nProbability of a comment being scored each category')
print(output['predicted_dqi'].value_counts(1))
```

```
# Import Libraries

from sklearn.datasets import fetch_20newsgroups
from sklearn.decomposition import TruncatedSVD
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.feature_extraction.text import HashingVectorizer
from sklearn.feature_extraction.text import TfidfTransformer
from sklearn.pipeline import make_pipeline
from sklearn.preprocessing import Normalizer
from sklearn import metrics
%matplotlib inline
import matplotlib.pyplot as plt
plt.style.use('ggplot')

from sklearn.cluster import KMeans, MiniBatchKMeans

import sys
from time import time
import pandas as pd
import re
from nltk.corpus import stopwords

import numpy as np


# Clean dataset
dataset = data_df = pd.read_csv("C:\\Users\\LabUser\\Desktop\\DataFolder\\TrainingData_Set\\stored\\unlabelled2.csv")
labels = dataset.columns


vectorizer = TfidfVectorizer(use_idf=True, max_features=1000, analyzer='word', ngram_range=(3,3))

def comment_to_words(raw_comment):
    if pd.isnull(raw_comment):
        return ""
    else:
        letters_only = re.sub("[^a-zA-Z]", " ", raw_comment)
        words = letters_only.lower().split()
        stops = set(stopwords.words("english"))
        meaningful_words = [w for w in words if not w in stops]
        return " ".join(meaningful_words)

clean_train_comments = []

dataset["cleaned_comment"] = dataset["comment"].apply(lambda x: comment_to_words(x))

fit_vectorizer = vectorizer.fit_transform(dataset['cleaned_comment'])
svd = TruncatedSVD(n_components=100)
normalizer = Normalizer(copy=False)
lsa = make_pipeline(svd, normalizer)
fit_lsa = lsa.fit_transform(fit_vectorizer)


# Implement KMeans

km = KMeans(n_clusters=5, init='k-means++', max_iter=100, n_init=10,
                verbose=True)
km.fit(fit_lsa)

print("Silhouette Coefficient: %0.3f"
      % metrics.silhouette_score(fit_lsa, km.labels_, sample_size=1000))


print("Top terms per cluster:")

original_space_centroids = svd.inverse_transform(km.cluster_centers_)
order_centroids = original_space_centroids.argsort()[:, ::-1]

terms = vectorizer.get_feature_names_out().tolist()
for i in range(5):
    print("Cluster %d:" % i, end='')
    for ind in order_centroids[i, :10]:
        print('; %s' % terms[ind], end='')
    print()
```

```python
# Visualize top 15 3-grams by importance
idf = vectorizer.idf_
idf_dict = dict(zip(vectorizer.get_feature_names_out().tolist(), idf))
idf_df = pd.DataFrame.from_dict(idf_dict, orient='index')
idf_df = idf_df.sort_values(by=0, ascending=False)
for i in range(5):
    df = pd.DataFrame(columns=['ngram', 'tf-idf-score'])  # Initialize df with the same structure as df2
    for ind in order_centroids[i, :15]:
        df2 = pd.DataFrame([[terms[ind], idf_df[0][terms[ind]]]], columns=['ngram', 'tf-idf-score'])
        df = pd.concat([df, df2], ignore_index=True)
    df = df.sort_values(by='tf-idf-score', ascending=False)
    plt = df.plot(kind='barh', legend=None, color='purple')
    plt.invert_yaxis()
    plt.set_yticklabels(df['ngram'])
    plt.set_title("Top 15 3-grams by importance: Cluster " + str(i))
    plt.set_xlabel("TFIDF Score (importance in dataset)")
    plt.set_ylabel("3-grams")
```

Appendix 6

Template Qualitative Critical Discourse Analysis of Telegram Messages

Description – Textual Analysis [Box 3 Text]		
Analysing the Visual Signs		
Time of Posting:		
Number of Views		
Number of Charts		
Include media		
Include term		
Discourse quality index		
Participation		
Level of justification?		
Content of justification		
Respect		
Counterarguments		
Constructive politics		
Verbal Processes		
Transitivity analysis of the text	Activity	
Material Processes (Doing, creating) → actor + goal (active vs. passive voice)		
Mental Processes (Feeling, Thinking, Perceiving) → Senser + phenomenon		
Relational Processes: (Being, Having) (is, has)		

Behavioral Processes: (Physiological, Psychological) (ex. breathe: smile)		
Verbal Processes: → sayer + what is said + (receiver)		
Existential Processes (ex. the world is round)		

Process of production and interpretation	
Interpretation – Processing Analysis (Text and discourse) [Box 2 Discourse Practice]	
Production	
Is there an obviously purpose of the message?	
Textual Hybridity	
Which or what kind of narrative is used?	

Condition of production and interpretation	
Explanation – Social Analysis [Box 1 Social Cultural Practice: situational; institutional: societal]	
Power Dynamics	
Implicit or explicit power dynamics	
Marginalization: implicit or explicit of a group?	
Discourses	
What ideologies are being promoted or wanted to achieve with the message?	