ENCODE

D3.2

Detailed methodology of the social networking analysis

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Dissemination Level: PU - Public
Lead Partner: PBY
Due date: 31.10.2024
Actual submission date: 31.10.2024

PUBLISHED IN THE FRAMEWORK OF

ENCODE – Unveiling emotional dimensions of politics to foster European democracy

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REVISION AND HISTORY CHART

VERSION	DATE	EDITORS	COMMENT
0.1	02.09.2024	PBY	ToC set up
0.2	11.10.2024	PBY, UWR	First draft completed for review
0.3	18.10.2024	UNIVIE	Reviewed
0.4	28.10.2024	PBY	Comments addressed and sent for final review
1.0	31.10.2024	ASM	Submission to Participant Portal

DISCLAIMER

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EXECUTIVE SUMMARY

Deliverable 3.2 (D3.2) – Detailed methodology of the social networking analysis is the second deliverable for work package (WP) 3 - Analysing Social Media Communication. The overall aim of the WP is to analyse the interrelationship between emotions, values and identities in narratives by collecting a vast amount of social media discussions. The first step to achieve this was to identify and summarize the state of the art of emotion and sentiment detection techniques for text analysis, which was done in D3.1. D3.2 covers the next step in the process: to define a scope for the research, and to set up a methodological framework for data extraction and analysis.

We will specify the data to be collected and the code to be implemented across different platforms (Facebook, Instagram, and TikTok). The initial version (V1) of the query search will be pretested into the languages of the pilot countries. Subsequently, a second version (V2) will be developed and iterated to obtain an optimal research corpus. Additionally, this process will include an overview of the key Natural Language Processing (NLP) and Artificial Intelligence (AI) techniques to be used, along with steps for quantitative analysis.

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1. INTRODUCTION

1.1 THE ENCODE PROJECT

The ENCODE project, titled "Unveiling Emotional Dimensions of Politics to Foster European Democracy," aims to explore and decode the role of emotions in political discourse and their impact on democratic processes. Recognizing that emotional appeals have significantly influenced political movements and voter behaviour, ENCODE seeks to understand the interplay between emotions, values, and identities. The project's primary goal is to create new positive narratives that can foster trust and engagement in European democratic processes, thereby counteracting the negative emotions that often dominate political discussions. Through innovative methodologies, including social media sentiment analysis, biometric research, and surveys, ENCODE aims to provide policymakers with tools and strategies to better incorporate the emotional needs of citizens into governance, ultimately enhancing democratic resilience and fostering a more inclusive political environment.

1.2 OBJECTIVES OF DELIVERABLE

This deliverable outlines the methodology for the work to be conducted in WP3 - Analysing Social Media Communication. The primary goals of this WP focus on the transformation of communication through social media, while addressing concerns about political interference and the spread of untrustworthy news and disinformation. By examining the relationship between emotions, values, and identities in social media narratives, we aim to gather extensive data from online discussions. Additionally, analysing emotions connected to disinformation will offer key insights into the evolving European political and cultural landscape and its impact on emotions in politics, as well as societal cohesion issues.

In this deliverable we will outline a comprehensive methodological framework for collecting, processing, and analysing social media data, including both the syntax and code. It starts out with an overview of the scientific literature on emotions, values and identities and the research questions we aim to investigate in the work. Following this, we will detail the specific data to be gathered and the code to be applied across various platforms (Facebook, Instagram, and TikTok). The first version (V1) of the algorithm will undergo pretesting before being translated into the languages of the pilot countries. Thereafter, a second version (V2) will be developed and translated accordingly. Additionally, it will provide an overview of the key NLP and AI techniques to be implemented as well as some directions for quantitative analysis.

1.3 STRUCTURE OF THE DOCUMENT

The deliverable is structured in the following main sections:

- Section 2 – Provides an overview of relevant research done on emotion analysis as well as research questions.
- Section 3 – Describes the data collection procedure for the different relevant data sources.
- Section 4 – Outlines the NLP and AI techniques used to automatically tag the data.
- Section 5 – Offers an initial outline of the quantitative analysis that will be done on the automatically coded data.

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- Section 6 – Serves as a conclusion to the deliverable.

1.4 RELATION TO OTHER TASKS

This task and deliverable builds on the work conducted in T3.1, which was reported in D3.1, and describes a generic process for the work to be done in the future work. D3.1 provided the state of the art for conducting emotion and sentiment detection using text data. Therefore, knowledge generated in D3.1 is used as input for this deliverable as well. its output feeds straight into the work in all tasks of the WP3. In addition, D3.2 describes the work to be done in T3.3 - Data collection and sentiment analysis of emotions in all countries, since procedures for data collection, automatic tagging and quantitative analysis are outlined. Finally, it serves T3.4 - Establishing a catalogue of best practices, since the best practices will be generated from the data collected and analysed in T3.3 and thus from the methodology that is defined in this deliverable.

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2. BACKGROUND

The overall of aim of this research is to study the interplay of emotions, values and identities as expressed in political discussions on social media. Therefore, we start by providing a background based on the research conducted on emotions, values and identities in this Section, in order to fundament the development of the methodological framework. It starts out with the theoretical background in Section 2.1 providing a framework for how to understand emotions, affects, and values. Subsequently, Section 2.2 turns to the empirical research conducted studying emotions, values, and identities using social media data. Finally, the scope and aims of our research is outlined in Section 2.3, in which we provide the research questions.

2.1 THEORETICAL BACKGROUND

This section outlines key concepts—affect, emotion, value, and belief—focusing on how they are studied across disciplines. Affect and emotion are central to affective sciences but have broader relevance, particularly in social and political contexts, which is the focus of ENCODE. Additionally, ENCODE examines values and beliefs from a social sciences perspective (see Scarantino & de Sousa, 2021). The goal is to define these concepts clearly to guide the development of the methodological framework for future research in the project, exploring their intersections and ensuring precise boundaries. It is a summarized version of the general concepts outlined for the ENCODE project. The full version can be found in D2.1 - Key ENCODE's concepts and their intersection.

2.1.1 EMOTIONS AND AFFECTS

We start by distinguishing between *emotion* and *affect*, two key concepts for ENCODE. Affect theory, rooted in biology and the "affective turn," focuses on bodily, impulsive, and unconscious experiences like anxiety, which are fluid and unstable. These affects can trigger political behavior and spread rapidly, sometimes evolving into enduring political passions (Eklundh, 2019, ch. 1).

In contrast, emotions are more conscious, intentional, and tied to specific objects, attaching meaning to affects (Hoggett & Thompson, 2012, pp. 2–3). Theories of emotions include:

- Naturalist theory (Darwin and James) views emotions as biological and universal.
- Cognitivist theory (Nussbaum, Lazarus) links emotions to individual judgments and beliefs.
- Constructivist theory (Durkheim) sees emotions as socially constructed, learned, and shaped by culture.

While the naturalist approach is not suited to our research, the cognitivist and constructivist theories are more fitting due to their social and political research. Hoggett and Thompson offered an interesting typology of political feelings (2012, pp. 7–12). They distinguish:

1. Positive moral emotions – feeling states which attach people to objects of emotions. Examples: sympathy, concern, compassion and forgiveness.
2. Negative moral emotions – feeling states separating us from the objects of our emotions. Examples: disgust, contempt. Negative moral emotions drive moral

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panics, that is, widespread hostility towards some group because of their imagined profile.

3. Positive feelings (of attraction) – good feelings which impact public spheres:
    a. *enhancing social relations* – examples: trust, love, gratitude. In this context, only trust has been studied which resulted in well-known research findings on social capital, social networks and contracts.
    b. *expressing positive relations to people or ideas that we consider "higher"* – examples: admiration, love, awe. An illustration are feelings to political leaders.
    c. *"Optimistic affects"* [1] – unformed feelings resembling affects, examples: hope, happiness, enthusiasm, joy, optimism. They might drive millenarian ideas such as communism, but also serve as "positive illusions" which contribute to our well-being.
4. Negative feelings (of repulsion) – negative feelings in public life:
    a. *resentment* – a set of negative feelings directed at others, including hatred, envy, malice, spite and loathing. Nowadays resentment has been identified as a source of authoritarian populism.
    b. *intangible negative feelings* – feelings towards such abstract objects as life or time; examples include cynicism, pessimism and despair.
5. Feelings associated with loss – these are such feelings as: grief, disappointment, disillusionment, sorrow, sadness, melancholy. In social life, they accompany social and economic changes, e.g., urbanization, migration, development.
6. Feeling associated with hurt – the feelings that emerge in groups experiencing negative emotions such as hatred or disgust.
7. Feelings associated with injustice – the feelings that fuel protests, including anger, grievance, outrage, resentment.
8. Feelings related to 'flight' – this type of feelings refer to fear, anxiety, terror which might produce paranoia

2.1.2 VALUES AND BELIEFS

In this section we explore the relationship between values, beliefs, emotions, and affects, emphasizing the complexities in their interconnections. While both cognitivist and constructivist approaches agree that emotions stem from values and beliefs, they differ in their views on the origin: cognitivists see these as individual choices, while constructivists attribute them to socio-cultural influences (Koschut, 2020, pp. 7–8).

Values, defined as abstract goals or motivations, play a central role in shaping identity, societal changes, and political behaviour (Scharfbillig et al., 2021, p. 22). The European Commission's report highlights the stability of values, their role in polarization, and how they shape collective actions. Various empirical studies on values, including those by Milton Rokeach (Kaiser, 2024) and Shalom Schwartz (Beckers et al., 2012)., distinguish between different types of values. Schwartz's typology of values is particularly relevant for ENCODE's research on polarized societies. Schwartz distinguished the following types of values: self-

[1] The term is coined by us because the Authors do not provide a specific term for that category.

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enhancement (power, achievement), openness to change (hedonism, stimulation, self-direction), self-transcendence (universalism, benevolence), and conservation (tradition, conformity, security) (Beckers et al., 2012).

Beliefs, on the other hand, are more changeable and weaker than values but are still closely linked, often seen as a type of moral belief (Kaiser, 2024). While some scholars criticize value theory for being abstract and untestable, recent critiques, like those by Matthias Kaiser (2024), argue that emotions and affects might offer more insight into human behaviour. Ultimately, the relationship between values, beliefs, emotions, and affects forms a complex, interrelated network rather than clear, independent drivers of action.

2.2 EMOTIONS, VALUES AND IDENTITIES IN SOCIAL MEDIA ANALYSIS

In the last decade, social media platforms have transformed the landscape of communication, particularly political communication. They have provided a powerful platform for the dissemination and consumption of political information, under the promise of empowering democratic values. However, the increasing reliance in such means of political communication is also giving rise to concerns about polarization and the rise of disinformation (European Parliament. Directorate General for Internal Policies of the Union., 2023). This increasing reliance on social media by political elites, influencers, and citizens has significantly altered how political content is created, shared, and interpreted. While sentiment analysis has been extensively used to study the tone and polarity of social media content, there has been less focus on understanding the role of specific emotions in shaping political discourse. This gap is particularly pronounced when considering the spread of populism and the proliferation of untrustworthy news, which rely heavily on emotional appeals to engage and mobilise audiences (Weismueller et al., 2022). This is critical as several studies highlight how cognition and emotion have become equally important in shaping individuals' political judgment and opinions (Caiani & Di Cocco, 2023; Scharfbillig et al., 2021; Marquart et al., 2022). Furthermore, Widmann (2021) argues how these implications are concerning for democracy, as such emotionally charged rhetoric can deepen societal polarization, negatively stereotype minorities, and erode democratic norms, highlighting the need for more nuanced analysis and responses to the emotional tactics in political communication.

2.1.1 SENTIMENT VS. EMOTION IN SOCIAL MEDIA ANALYSIS

Research on sentiment analysis has become highly extensive, particularly in the context of social media. Sentiment analysis is a natural language processing method that is used to classify text as expressing positive, negative or neutral feelings (Gillies & Barney, 2024). Pang & Lee (2008) foundational work on sentiment analysis has driven much of this research, focusing on categorizing social media content into positive, negative, or neutral sentiments. The proliferation of sentiment analysis tools and techniques has enabled researchers and businesses to gauge public opinion, analyse market trends, and monitor political sentiment. Crabtree et al. (2020) use Linguistic Inquiry and Word Count (LIWC) to perform automatic sentiment analysis on political party manifestos. These types of lexicon-based analysis have been replaced by more advanced Machine Learning methods, Hasan et al. (2018) use Naïve

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Bayes and Support Vector Machine (SVM) algorithms to evaluate the sentiment (positive, negative, neutral) of Twitter profiles.

Despite these advances, sentiment analysis often simplifies emotional expressions into broad categories, which fails to capture the complexity of human emotions. Recent research by Bollen et al. (2021) highlights this limitation, showing that social media users express a wide array of emotions beyond simple sentiment categories. Their work indicates that emotions like fear, anger, and joy can spread through social networks in distinct patterns, influencing user behaviour and information dissemination. The research on valence (positive or negative) is extended and well documented however, it reflects the need to move beyond basic sentiment analysis to understand the emotional undertones and subtleties within social media text (Widmann, 2021). There is a need to expand on emotion theories that go beyond defining the human emotion's numerous dimensions and their role in online interactions. Widmann (2021) also identifies how political actors use different emotional appeals for different purposes, emphasising the strategic use of specific emotions in political discourse, particularly by populist and radical-right actors. Their results strongly emphasize the need to move away from sentiment analysis towards the investigation of discrete emotions.

2.1.2 VALUES IN SOCIAL MEDIA ANALYSIS

The analysis of values in social media revolves around understanding the underlying cultural and personal values reflected in users' communications. These values are deeply embedded in the way individuals express their opinions, beliefs, and identities on social platforms. Tools like values text-mining and media-monitoring have been developed to analyse large datasets, helping policymakers and researchers identify relevant values and how they are communicated (Scharfbillig et al., 2021). Values, which refer to core principles or standards that guide behaviour, have been studied primarily in specific contexts like consumer behaviour and political ideologies. Schwartz's (1992) theory of universal values has provided a foundational framework, yet its application to social media has been limited. In political contexts, particularly with the rise of populism, social media has become a critical space where values are communicated and contested. Research by Gerbaudo (2018) examines how populist movements use social media to amplify values such as nationalism, anti-elitism, and protectionism. These values are often expressed through emotionally charged rhetoric, creating a powerful resonance with audiences. Van der Meer et al. (2023) use Schwartz's theory to evaluate if the difference in personal values is indicative of disagreement in online discussions, using annotated corpuses to fine-tune two pre-trained transformers (BERT and RoBERTa). However, the systematic study of how these values are articulated and reinforced across different social media platforms is still lacking. There is a need for a deeper analysis of the interplay between values, emotions, and identity in political discourse on social media, particularly how these elements are mobilized to support populist agendas (Caiani & Di Cocco, 2023).

2.1.3 IDENTITIES, POLITICS, AND THE ROLE OF UNTRUSTWORTHY NEWS

Identity formation and presentation on social media have been extensively explored, particularly through the lens of self-presentation (Goffman, 2007) and identity construction within specific communities. However, the intersection of identity with political discourse, especially in the era of untrustworthy news, is an emerging area of research that requires further attention. Identities play a critical role in shaping political behaviour and polarization,

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particularly as partisan identities have come to dominate the political landscape. These identities integrate multiple aspects of an individual's social and cultural beliefs, intensifying political conflicts as people align more strongly with their "in-groups" and become more resistant to opposing viewpoints (Scharfbillig et al., 2021). The rise of identity politics, where political interests are increasingly framed through the lens of specific group identities such as race, gender, or religion, has further fuelled polarization, shifting the focus from traditional economic issues to cultural conflicts. Research by Marwick and Boyd (2011) investigates how social media users navigate their identities in digital spaces, balancing authenticity with audience expectations. This dynamic becomes more complex in political contexts, where identity performance can be influenced by external pressures and the spread of misinformation (Grasso, 2023).

Untrustworthy news exploits these deeply ingrained identities by reinforcing existing biases through selective exposure, where individuals consume information that aligns with their beliefs. This creates echo chambers that amplify misinformation, deepening political divisions and making it more difficult for individuals to engage with diverse perspectives (Weismueller et al., 2022). The interaction between identity-driven politics and the spread of untrustworthy news thus poses significant challenges to democratic discourse and social cohesion (Scharfbillig et al., 2021). The role of emotions in the spread of untrustworthy news has been highlighted in studies by Vosoughi et al. (2018), who found that false news spreads faster and more widely than true news, primarily because it elicits stronger emotional reactions. This research underscores the importance of understanding the emotional mechanisms at play in the dissemination of untrustworthy news and their implications for identity formation and political behaviour. Further, Wodak (2015) explores how populist leaders exploit emotions and identity in their rhetoric, using social media to create a sense of in-group solidarity while demonizing out-groups. This strategy often involves the spread of untrustworthy news, which taps into existing emotional and identity-based vulnerabilities among users.

2.1.4 GAP ANALYSIS – A TRANSVERSAL ANALYSIS OF EMOTIONS, VALUES AND IDENTITY IN SOCIAL MEDIA

While sentiment analysis is highly developed, a significant gap remains in the nuanced analysis of emotions on social media platforms. Therefore, future research should focus on developing tools that capture a broader range of emotional expressions and understand their role in driving user engagement and the spread of information, particularly in political contexts, exploring the relationship between values, emotions, and identities. There is a need for more systematic research on how political values are communicated, resonated with, and reinforced across different social media platforms. The interplay between emotions, values, and identities in political discourse, particularly in the spread of untrustworthy news, is an emerging area that requires more comprehensive research. Developing interdisciplinary frameworks that integrate these elements could provide deeper insights into the social dynamics of digital politics.

Another key aspect is the subjects of such analysis, extensive research has been done on different variations of emotions (or sentiment), values and identities relying on traditional supports such as party manifestos or political leaders' speeches (e. g. Caiani & Di Cocco, 2023). A focus on social media brings a new perspective as it has been argued along this section. Emotional communication in online platforms has opened new underlying paths of linking media content to emotional reactions in citizens' political behaviour and attitudes via affective mediation (Marquart et al., 2022). However, most research on political discourse on

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social media has focused on more traditional sources, such as political leaders and mainstream media platforms (Munoz & Towner, 2022; Widmann, 2021). Weismueller et al. (2022) propose the study of influencers to dive deeper into the network instructions of users, and the diffusion of emotional content, understanding impact as sharing behaviour. However, very scarce research has been carried out on the general population's emotional behaviour on social media and how its political views and values take part in the polarization of society online. Furthermore, most of the social media research has been carried out on Twitter, Facebook or Reddit, using textual analysis, with an important gap in new platforms such as TikTok, and multimodal analyses of image and text such for the case of Instagram posts.

2.3 FOCUS OF STUDY AND RESEARCH QUESTIONS

The overall aim of this research is to study the interplay of emotions, values and identities as expressed in political discussions on social media. The research will cover the following six European countries: Poland, Bulgaria, Denmark, Austria, North Macedonia, Bosnia and Herzegovina. The work aims at answering the following research questions:

- What role do emotions play in the online discourse in relation to the values and identity of the user?
- What emotions and values are conveyed in untrustworthy news compared to other news in social media?
- Which affects and emotions are most triggering in terms of generating responses and reactions in social media?

We aim to build a methodological framework that centres the analysis on certain political themes and analyse different types of users where possible (see Section 3 for which data sources allows for this). Particular users, such as politicians as well as trustworthy and untrustworthy media outlets can be identified from partner country expertise and their social media activity can be extracted from the different platforms. Additionally, we aim to analyse online discussions in which case we will analyse posts and their comments as well as groups on Facebook. Together, this should generate an understanding of the interplay of emotions, values and identities as expressed on social media and how different actors convey different emotions and values and what discussions and reactions they generate. As such, this work will provide an initial descriptive overview of the importance of emotions, values and identities conveyed in political discussions as well as for the spreading of untrustworthy news and consequently, democratic processes.

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3. DATA COLLECTION

To address this research questions that aim to study the interplay of emotions, values and identities as expressed in political discussions on social media, we developed a methodological framework that defines the unit of analysis and the characteristics we will study for each social media platform. With that aim, in Section 3.1 we characterise the different social media platforms we pose to use for the analysis, understanding the content, main features, demographic reach and API services to extract the data. Once we have defined the platforms in Section 3.2, we dive into the information available for analysis, determine the different units of analysis available in each specific platform and describe how it can be extracted by defining the first search string. After the first search, we describe the iterative process of refining the search to obtain accurate high-quality data for the purpose of our study in Section 3.3.

3.1 DATA SOURCES

We explore different social media platforms as suitable candidates to study the interrelations of emotions, values and identities as expressed in political discussions. The platforms chosen for this methodological framework are TikTok (Section 3.1.1), and Meta platforms Instagram and Facebook (Section 3.1.2). They were selected due to their relevance for the political debate, widely extended use, distinct features and its research tools and protocols for access. In this Section, we will dive into the specific features of each platform the type of content generated and the demographic reach of users.

3.1.1 TIKTOK

TikTok offers a rich and dynamic repository of user-generated content that is particularly valuable for studying social, political, and cultural phenomena. The platform is characterized by its short-form video content, which ranges from 15 seconds to 3 minutes, allowing for rapid dissemination and consumption of information. As a social media platform with a global user base exceeding 1 billion monthly active users, TikTok provides an extensive dataset that reflects a diverse range of perspectives, behaviours, and interactions (Herrman, 2019; SEO.AI's Content Team, 2024).

The platform's API offers access to certain data points such as user profiles, video metrics, comments and captions for academic institutions under TikTok's terms of service and ethical research standards (TikTok, 2024). This access is granted under a clearly defined research proposal that shows that the access requested is needed for, and proportionate to, the purpose of that research, commit to fulfilling data security and confidentiality requirements (including taking steps to protect personal data) and being able to provide evidence that the research went through an ethical research review. TikTok will assess this request in a period of 4 weeks to grant access to the research team.

- Content: TikTok's content is incredibly diverse, encompassing a wide array of topics including politics, social justice, personal expression, entertainment, and everyday life. Users create videos using a variety of multimedia elements such as music, text overlays, visual effects, and voiceovers, which contribute to a multifaceted representation of ideas and emotions (Lee & Abidin, 2023). This diversity makes TikTok an ideal platform for studying complex social dynamics like democratic engagement

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and emotional expression.

- User interaction and "For You Page": TikTok's interactive features, such as likes, comments, shares, duets, and stitches, provide rich data on how users engage with content. These interactions can be analysed to understand the spread of ideas, the formation of public opinion, and the role of emotions in shaping discourse. The platform's algorithm-driven "For You Page" (FYP) curates content based on user preferences (Bhandari & Bimo, 2022), which can be studied to understand the impact of algorithmic curation on political and emotional engagement. Furthermore, this FYP feature plays a crucial role in its rapidly evolving trends, challenges, and viral content. These phenomena often serve as flashpoints for broader social and political discussions, making TikTok a valuable source for tracking real-time shifts in public sentiment and the emergence of grassroots movements (Lee & Abidin, 2023). However, it also leads to the clustering and segregation of communities, showing only content that abides by one's values and beliefs, tending to the polarization of individuals (Gilbert, 2024). This feature can be leveraged to study how democratic ideals and emotional narratives gain traction and influence in a polarized online ecosystem.
- Demographic reach: TikTok's user base is vastly composed of young people, with a significant proportion of users aged between 16 and 24. This demographic is particularly engaged in social and political issues, often using the platform as a means of activism and expression. As a result, TikTok provides insight into the attitudes, emotions, and behaviours of younger populations, who are increasingly shaping political discourse (Karimi & Fox, 2023).

3.1.2 META – FACEBOOK & INSTAGRAM

Meta Platforms, Inc. (formerly Facebook, Inc.) is a leading technology company that owns Facebook, Instagram, WhatsApp, and Messenger. Founded in 2004 by Mark Zuckerberg, Meta rebranded in 2021 to emphasize its focus on building the "metaverse"—a virtual reality space for social interaction. Meta's platforms are central to global communication, with billions of users engaging daily (Rourke, 2023). Facebook and Instagram, in particular, are key sources for social interactions, that lead to the development of an intrinsic online political, and cultural discourse.

Meta has partnered with the Inter-university Consortium for Political and Social Research (ICPSR) at the University of Michigan to share public data from Meta's platforms. In order to obtain access to Meta's platforms data researchers have to do the application through their SOMAR platform detailing the research proposal. Researchers can retrieve posts, comments, user interactions, and other relevant content for analysis. The API service supports filtering data based on keywords, hashtags, user demographics, and more, making it a powerful tool for targeted data collection. Furthermore, data is processed in a close research environment online, equipped with Python and R, nevertheless, it is unclear the full extent and functionalities of such environment (Meta, 2024).

Facebook is one of the largest and most influential social media platforms in the world, with over 2.9 billion monthly active users as of 2024 (Statista, 2024b). It serves as a comprehensive source of data for analysing social, political, and emotional dynamics due to its diverse user base, extensive content, and rich interaction features.

- Content: Facebook hosts a wide range of content, including text posts, images, videos, live streams, and shared links. Users engage in both public and private

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discussions, making the platform ideal for studying various forms of discourse related to democracy, such as political discussions, activism, and community organizing.

- User Interaction, political engagement and mobilization: Facebook's features, such as likes, comments, shares, tagging, and reactions (e.g., love, angry, sad), provide valuable data for analysing emotional responses and the spread of information. The platform's reaction buttons can be useful for understanding the emotional tone of user interactions (Ha et al., 2017). Facebook Groups and Pages are central hubs for community-driven discussions and mobilization around specific causes or interests. These spaces often host debates, share news, and organize events related to democratic participation, dissident identities movements and partisan support circles, serving as means to evaluate political engagement and social mobilization (Kavtaradze, 2018).
- Demographic reach: Facebook's user base is diverse, encompassing various age groups, geographies, and socio-economic backgrounds. However, this varies vastly between countries. Facebook adoption and usage patterns, reveal minimal differences between older and younger adults in North America and Northern Europe, while in Asian countries, gender differences in adoption decrease with age due to socioeconomic factors. Women generally have larger networks of close friends than men and are more likely to use Facebook, especially if living away from their hometowns. These findings highlight the importance of considering demographic variables like age and gender when analysing digital platform usage, suggesting that qualitative differences in how men and women use Facebook are significant (Gil-Clavel & Zagheni, 2019).

Instagram is a visually oriented social media platform, with over 1.4 billion monthly active users (Statista, 2024a). It is primarily focused on photo and video sharing, making it a key platform for analysing visual communication, emotional expression, and the aesthetics of democratic activism. Nevertheless, posts also include captions and hashtags that are relevant from a textual analysis perspective.

- Content: Instagram's emphasis on images and videos makes it a highly unidirectional platform, usually used by brands, influencers and celebrities, as it is conceived as a white platform that prioritizes visually pleasing, lifestyle-oriented, and apolitical content over discourse-heavy or confrontational material. Nevertheless, some political movements, protests, and social causes, as well as far-right parties have leveraged this platform to expand their message to other public relaying in emotionally charged imagery, captions and sort videos (Mashtoub, 2023; Poulakidakos, 2020).
- User Interaction, hashtags, stories and reels: Similar to Facebook, Instagram offers various forms of user interaction, including likes, comments, shares, and direct messages. These interactions can be analysed to understand user engagement with democratic content and the emotional reactions it elicits. Hashtags play a crucial role on Instagram in organizing content around specific themes or movements. Hashtags like #Democracy, #Vote, #Protest, and #Activism allow researchers to track the spread of democratic discourse and the emotional tone associated with these discussions (Al-Rawi, 2021). Trending hashtags can also indicate emerging issues and collective sentiments. Furthermore, Instagram Stories and Reels are short-lived or short-form video content features that have become popular for sharing immediate, often emotional, reactions to events (Vermeer & Van Den Heijkant, 2024). These features are instrumental in understanding how users express emotions in real-time, particularly in response to political events.

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- Demographic reach: Instagram's user base tends to be younger and more visually oriented, with a strong presence among millennials and Gen Z. This demographic profile makes Instagram particularly valuable for studying how younger generations engage with and express emotions about democratic issues, as well as how new political movements arise and engage these users (Jaramillo, 2021; Poulakidakos, 2020). Citizens follow political leaders on Instagram primarily for information and entertainment, with motivations influenced by demographic factors such as age and political engagement, highlighting Instagram's significant role in political communication (Parmelee & Roman, 2019).

3.2 DATA EXTRACTION

Once having characterized the social media platforms we intend to use for the study and following the approval of our data access request. In this Section, we explore the categories of data accessible through the API for each platform and the unit of analysis it generates. Secondly, we will look at the steps of how to implement a first search string into the API systems of each of the platforms, in order to extract the desired data with its associated fields and metadata. In Subsection 3.2.1 we will address TikTok's API and in Subsection 3.2.2 we will tackle the features of Meta Content Library API.

3.2.1 TIKTOK API

The TikTok API is a set of tools and endpoints provided by TikTok that allow researchers to access certain data from the platform. While the API is primarily intended for business and marketing purposes, researchers can use it to collect specific types of data relevant to user engagement, video content, and user interactions around topics of interest.

3.2.1.1 TYPES OF DATA ACCESSIBLE THROUGH THE API

Through its codebook[2] TikTok gives a detailed description of the data available to researchers via its API. There are several units of analysis available:

- VIDEOS: a public TikTok video posted by a public creator (who is aged 18 and over), who wants to expose their videos to all users of TikTok and do not belong to Canada. Among the metadata available ID, creation time, video description and region code.

CATEGORY	DESCRIPTION	ANALYTICAL USE
VOICE_TO_TEXT	Voice to text and subtitles (for videos that have voice to text features on, show the texts already generated)	Will serve as our unit of analysis as this textual transcription of the video will serve to categorize the emotion and value of the video using our LLM.
USERNAME	Username of the video creator, will be anonymized with a unique id.	Can be used to link several videos of the same author and create an aggregated value profile.

[2] https://developers.tiktok.com/doc/research-api-codebook

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REGION CODE	A two-digit code for the country where the video creator registered their account.	Will allow us to filter the content in each of the countries under study (DK, BG, PL, BA, MK, AT).
HASHTAGS	Hashtags used in the video	You can pull data on specific hashtags (e.g., #Democracy, #Elections, #Vote) to track how often they are used and in what context. This will form our search string.
INTERACTIONS	"Like Count", "Comment Count", "Share Count" and "View Count"	These metrics measure the interaction and reach of a given video and can give us valuable input into how users react to democracy-related content.

Table 1 Categories of data available for video (unit of analysis) through TikTok API for researchers

- COMMENTS: the information provided here includes text extracted from comments and a serial number (i.e. comment IDs) that help identify original comments posted on a video and any replies to comments. To protect the privacy of our users, other information is removed.

CATEGORY	DESCRIPTION	ANALYTICAL USE
TEXT	This is the actual text of the comment entered on a video. To protect the privacy of our users, other information is removed.	This textual information can be used to analyse the type of emotions and values expressed in the comments of a given video.
ENGAGEMENT	"Reply Count" and "Like Count" for each comment.	Can be used to measure the reactions generated by a given video, further complementing the text analysis
VIDEO_ID	This is the video ID for which the comment was entered.	It serves to trace back the original video and link other comments.

Table 2 Categories of data available for comments (unit of analysis) through TikTok API for researchers.

- USERS: User information of all TikTok users that have set their account to public and are aged 18 and over. This can be useful to garner further insights in particular political actors' use of TikTok, and the engagement they generate and further define the values and political identity.

CATEGORY	DESCRIPTION	ANALYTICAL USE
ENGAGEMENT	"Following Count", "Likes Count", "Video Count" for the user's profile	These metrics measure the interaction and reach of a given user.

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IS VERIFIED	This returns the information on whether the user has been verified. If the user has a blue tick, this variable will return a "true" in the response.	It gives insightful information on influence capabilities and official profiles.

Table 3 Categories of data available for users (unit of analysis) through TikTok API for researchers.

- Other units of analysis available: Liked Videos, Reposted Videos, Pinned Videos, Query Followers List, Query Following List. This later two can be used to query for a particular user follower and following list, making possible to establish connections among users.

3.2.1.2 STEPS FOR USING THE TIKTOK API

- Registration & Access: To access the TikTok API, you'll need to register for a TikTok Developer account and request API access. TikTok may review your application to ensure the API is being used for appropriate and compliant purposes, so outlining your research intentions may help with approval.
- Authentication: Once you have access, you'll need to authenticate API requests using OAuth tokens. This ensures secure access and retrieval of data.
- Data Retrieval:
    - Make API requests with the appropriate parameters (e.g., hashtag, region code, time range, keyword). Some examples of strings can be,
        - GET /videos?hashtag=#Democracy&hashtag=#Hope&max_results=100 – This string searches for videos that use the hashtag #Democracy and #Hope. The max_results=100 limits the output to 100 results.
        - GET /videos?hashtag=#Elections&start_time=2024-05-01&end_time=2024-06-30- This string retrieves videos tagged with #Elections during the peak election season (May to June 2024).

    This will be further fine-tuned in V2 of data extraction. Depending on the data volume, it may be needed to paginate your requests or set rate limits as per TikTok API policies.

3.2.2 META CONTENT LIBRARY AND API

Meta offers the Meta Content Library and API, a comprehensive tool that enables researchers to extract publicly available posts from Facebook Pages, Groups, and Instagram accounts. By leveraging this API, researchers can collect vast amounts of user-generated content related to specific topics, time periods, or geographic regions. The data included is subject to fulfilling asset or requirements:

- Facebook data includes the following publicly accessible content:
    - Posts on public Pages, public groups, public events
    - Posts on public profiles with a verified badge or 25,000 or more followers
    - Information about public Pages, public groups, public events and public profiles that meet the above criteria
- Instagram data includes the following publicly accessible content:
    - Posts from public business accounts and public creator accounts

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- Posts from personal accounts set to public with 25,000 or more followers
- Information about public Instagram accounts that meet the above criteria

3.2.2.1 TYPES OF DATA ACCESSIBLE THROUGH THE API

The Meta Content Library API allows researchers to extract various types of data that serve as units of analysis for social media studies, as detailed in the data dictionary[3]. The primary units of analysis include posts, users and engagement metrics.

- FACEBOOK POSTS: are the primary content generated by users and can take various forms, such as text updates, images, videos, links, and shared content from other users. Amoun the metadata available to study posts we can leverage:

CATEGORY	DESCRIPTION	ANALYTICAL USE
TEXT	The main body of the post, including text excluding tags.	This will serve as our unit of analysis to categorize the emotion and value of the video using our LLM.
CREATION TIME	The exact time and date when the post was created.	It enables researchers to conduct temporal analyses or study posts around specific events.
LANGUAGE	The content language of the Facebook post. Returns ISO 639-1 language code in 2-letter lowercase format.	Will allow us to filter the content in each of the countries/languages under study (DK, BG, PL, BA, MK, AT).
POST ENGAGEMENT	Interaction metrics like the number of likes and wow, haha, sad and angry reactions, shares, comments, and views.	These are useful for assessing public response and engagement.
POST OWNER	ID information	Will be used to trace the connection between the post and their author.

Table 4 Categories of data available for Facebook posts (unit of analysis) through Meta Content Library API.

- FACEBOOK COMMENT: the information provided here includes text extracted from comments and a serial number (i.e. comment IDs), they also identify the comment owners ID and the Parent Comment ID. The rest of the information is codified the same way as for posts.

- FACEBOOK PROFILES: while the API does not provide detailed personal information about individual users due to privacy constraints, it allows researchers to gather data from public and verified accounts. User-related data can be an important aspect of the analysis as we can gather information about:

[3] https://developers.facebook.com/docs/content-library-and-api/appendix/data-dictionary

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CATEGORY	DESCRIPTION	ANALYTICAL USE
PROFILE INFORMATION	Facebook profile categories (e.g., personal, business, organization), and other public details, such as about or intro texts.	Will be used to profile and categorize users.
ADMIN COUNTRIES	List of predicted primary country locations of the Facebook profile owner.	Will allow us to filter the content in each of the countries under study (DK, BG, PL, BA, MK, AT).
VERIFICATION STATUS	Possible values: not_verified and blue_verified.	Can be utilised to discern official accounts.
FOLLOWER COUNT	Number of users following a given profile page.	Provides a measure of the potential reach of a post or account's influence over time.

Table 5 Categories of data available for Facebook profiles (unit of analysis) through Meta Content Library API.

- INSTAGRAM POSTS: formed by an image or video with a caption text, have been the main content generated on Instagram since its creation. However, a shift in tendencies has widened the span of the content formats available on Instagram, mainly through stories, yet the period of 24 hours this content is posted excludes it from the Meta Content Library resources.

CATEGORY	DESCRIPTION	ANALYTICAL USE
TEXT	The main body of the post, including text excluding tags.	This will serve as our unit of analysis to categorize the emotion and value of the video using our LLM.
HASHTAGS	Hashtags included in the post caption.	They are often used to categorize content, and the API allows for retrieval based on specific hashtags, offering a way to track thematic discussions or trends over time.
CREATION TIME	The exact time and date when the post was created.	It enables researchers to conduct temporal analyses or study posts around specific events.
LANGUAGE	The content language of the Instagram post. Returns ISO 639-1 language code in 2-letter lowercase format.	Will allow us to filter the content in each of the countries/languages under study (DK, BG, PL, BA, MK, AT).
POST ENGAGEMENT	Interaction metrics englobe the number of likes and views.	These are useful for assessing public response and engagement.

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POST OWNER	ID information	Will be used to trace the connection between the post and their author.
MEDIA TYPE	The media type included in the Instagram post. Media types include albums, photos, videos and reels.	Will enable analysis on the different types of content published.

Table 6 Categories of data available for Instagram posts (unit of analysis) through Meta Content Library API.

- INSTAGRAM COMMENT: the information provided here includes text extracted from comments and a serial number (i.e. comment IDs), they also identified the comment owners ID and the Post ID. The rest of the information is codified the same way as for posts.

- INSTAGRAM ACCOUNT: while the API does not provide detailed personal information about individual users due to privacy constraints, it allows researchers to gather data from public and verified accounts. User-related data can be an important aspect of the analysis however the available information is limited.

CATEGORY	DESCRIPTION	ANALYTICAL USE
ACCOUNT TYPE	The type of public Instagram account. Creator, business, and personal accounts are valid types.	Can be utilised categorize user types.
IS VERIFIED	Whether the Instagram account has a verified badge. A verified badge in this context refers to accounts confirmed as authentic and not to those with a paid Meta Verified subscription.	It gives insightful information on influence capabilities and official profiles.
FOLLOWERS AND FOLLOWING COUNT	Count of accounts followed and count of accounts following a given user.	Provides a measure of the potential reach of a post or account's influence over time.
ACCOUNT INFORMATION	Including the name and username, will be anonymized with a unique identifier.	Can be utilised categorize user types. Will be used to trace the connection between the post and their author.

Table 7 Categories of data available for Instagram accounts (unit of analysis) through Meta Content Library API.

3.2.2.2 STEPS FOR USING THE META API

Using the Meta API to extract data for research involves a structured process that requires setting up access credentials, constructing queries, and refining the data retrieval process.

- Setting up access to the Meta API: to use the Meta Content Library API, once access is granted for research proposes

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  - Set up Open Virtual Private Network (VPN): Content Library API can only be accessed through a VPN. Researchers should install and configure the OpenVPN client and connect to the Meta Content Library VPN server.
  - Log in to the researcher platform URL: Log in to the site using your Facebook credentials access was granted. This will spin up an instance of JupyterHub server to use in the Researcher Platform.
- Formulating queries for data extraction: after gaining access, the next step involves constructing queries to extract relevant data. The Meta API allows researchers to specify various filters and parameters to ensure the extracted data aligns with the research objectives.
  - Create a Jupyter notebook: in order to enter the search queries, you can choose Pyhton3 or R as your query language.
  - Import the Content Library API client: all calls are made using the Content Library API Client. You only need to import the Content Library API client once per Jupyter notebook server session.
  - Define the search query and test it: the query will be based on a set of relevant keywords and hashtags a set time range and applying geographic and language filters. I must be noted that in version 4.0 of the API some search fields have been deprecated, new adaptations may be needed as the platform is updated.

We illustrate an example of a search using keywords "democracy" and a defined time period (from April 1st 2024 and June 30th 2024), for Facebook posts.

```
from metacontentlibraryapi import MetaContentLibraryAPIClient as client

client.set_default_version(client.LATEST_VERSION)

response = client.get(
  path="search/facebook_posts",
  params={"q": "democracy", "since":"2024-04-01", "until":"2024-06-30"}
```

For advance queries, the following rules apply:
- The following operators are supported: AND, OR, NOT.
  - Use an ampersand character (&) or a blank space to indicate AND.
  - Use a pipe character (|) to indicate OR.
  - Use a hyphen character (-) to indicate NOT. The en-dash and em-dash characters are not interpreted as substitutes for hyphens and are treated instead as keywords.
- For queries with multiple operators, NOT clauses are processed first, followed by AND, followed by OR. Imagine the terms grouped as if with parentheses.
- For clauses of equal precedence, there is a default left-to-right processing order.
- Grouping using parentheses is supported. Grouping can be used to modify the default processing order.
- You can use single-word keywords only (not phrases).
- Wild cards are not supported.
- Extra spaces around operators are ignored, so you can have them or not.

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3.3 V2 OF DATA EXTRACTION

After the design of the initial search string, the next step is to test and refine it in successive interactions. Based on the obtained results it would be useful to adjust the search string based on the pre-preliminary assessment of the query results. This process is a key element in the methodological framework to ensure that the data extraction process yields relevant and insightful, helping to avoid irrelevant or noisy data and providing a big enough sample.

3.3.1 INITIAL SEARCH STRING TESTING

Firstly, we have to run the initial query defined by the methodology in the chosen data sources (e.g., Facebook/Instagram and TikTok), with specific keywords translated into the 6 targeted languages (DK, BG, PL, BA, MK, AT). By analysing the preliminary dataset obtained from the query, we will evaluate whether it captures relevant discussions and emotional reactions related to democratic events or processes defined in the methodology. With that aim, we describe a set of questions that should be answered affirmatively referring to the data gathered via the search query.

- Data Quality: Assess the quality of the results. Are the posts or articles substantive enough to analyse? Avoid sources that are too short, irrelevant, or filled with noise.
    - Comprehensive: Are the results showing a substantive number of results?
    - Language and geographical distribution: Do they conform to the defined language and geographical constraints?
- Data availability: Do all the relevant fields defined in the methodology allow for filtering? Is there any unexpected limitation of the size of the query parameters or the sample?
- Randomize qualitative check: Observe whether the content is primarily related to the political focus defined, or if it drifts into unrelated subjects (such as sports or corporate governance). Are the results clearly tied to democratic processes? Are the emotional terms showing up in the correct context?
    - Relevance: Are the majority of the results directly connected to the topic? For instance, are you seeing discussions about voter reactions, political frustrations, or optimism about democratic reforms?

3.3.2 REFINING THE SEARCH STRING

Based on the initial results, the search strategy will be adapted, following these refinement strategies to increase data relevance and focus.

- Add/Remove Keywords:
    - Broadening search terms: If the results are too narrow or key discussions are missing, we should expand the keyword pool by adding related synonyms or alternative expressions.
    - Narrowing search terms: If the results are too broad or irrelevant, we should refine the string by removing ambiguous or overly broad keywords, in order to focus the scope of the study.
- Adjusting Time Frame:
    - Depending on your research focus, we may decide to limit or expand the time frame for data extraction, to better capture certain political events, and limit or increase the size of the sample.
- Modifying Filters:

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- **Content type:** we may refine the query by content type (e.g., only text posts, long-form articles, or multimedia posts) as our research is focused on the analysis of text.
- **Target profiles:** we may also want to obtain posts and interactions from specific users such as politicians or political parties. This can be directly extracted by querying about specific profiles.

3.3.3 ITERATING AND RE-TESTING

Successive iterations will follow the refinement of the query string. With each iteration, the goal is to improve the focus of the data, ensuring that the data gathered is aligned with the research objectives. Each test informs the next refinement, gradually adapting the query to produce high-quality content. If the refined search still returns irrelevant or incomplete data, further adjustments may be needed until the results meet your expectations, providing a reliable corpus to analyse. This iterative approach is key when analysing social media data as query results may vary a lot from what was expected in the methodology and the reality of the data available and the search capabilities of the available platforms.

Throughout the testing process, it's important to document every version of the search strings, reporting the changes made and why. This method of version control allows to track the evolution of your data extraction process, ensuring it can be replicated and reviewed. Keeping a record of the adjustments, such as adding specific emotional terms or narrowing the time frame, helps to maintain clarity and consistency in the research methodology. Reflecting on each change also provides insights into patterns within the data, such as which keywords yield the best results or whether certain filters improve relevance. By tracking these refinements, we not only ensure the accuracy of the search strategy but also gain a deeper understanding of the trends in the social media discussion on democracy.

3.3 CHALLENGUES AND ALTERNATIVE SCENARIOS

There is a potential issue regarding access to data, this is currently subject to strict protocols and complex legals terms. We aim at following the standard procedure to request access to the data both on Meta and TikTok, however it might be the case that access is not granted or that we are unable to meet the terms and conditions they propose to us for the use. If this was to happen, we could relay un publicly available datasets on emotions on social media, or from other projects in which members of the consortium participate. This will be detrimental in our ability to filter and set a time period for the analysis but should give us enough information to address the research questions proposed.

4.AUTOMATIC TAGGING

The core objective of this WP is to explore the role of emotions and values in political debates across Europe. The methodological framework we are building elaborates on the use of automated methods to classify emotions, affects, and values in large-scale textual data from social media. To accomplish this, we will employ a set of transformer-based LLMs, which will be fine-tuned using a manually annotated corpus or, if required due to the limitations of the

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data access constraints, a pre-existing fine-tuned model. This section outlines the steps involved in our methodology, including data filtering (Section 4.1), anonymization (Section 4.2), pre-processing (Section 4.3), and the detection of emotions, affects (Section 4.4.), and values (Section 4.5).

4.1 FILTERING OF DATA

The data for this analysis will be collected from social media platforms (TikTok, Facebook, and Instagram), as these platforms are hubs for real-time political discussions and reflect a wide range of public opinions. The filtering process will focus on further curating the search string result using further items to classify and categorize the data.

- Geographical and language filtering: as the analysis will be based in Austria, Bosnia Herzegovina, Bulgaria, Denmark, North Macedonia and Poland, geographical filtering will be key in assessing the differences between countries and identifying particular trends or debates. However geographical distribution may be too narrow in some cases a this may not be always available. In such cases, language can be used to filter posts for small countries whose official language is unique to them. Further language filtering will be used to analyse language-specific posts, and allow for easy manual annotation, using the official language of each country. Nevertheless, eventually, it could also be interesting to analyse the posts in other languages like English.
- Topic filtering: to ensure that the dataset reflects political discourse, specific keywords, hashtags, and phrases related to political events, policies, and issues (e.g., #Democracy, #EUElections, #RuleOfLaw) will be used.
- Platform-specific filters: each platform has unique affordances, and this will be reflected in the filtering process. For example, on TikTok, hashtags and comments may play a critical role in capturing politically charged conversations, while on Facebook, longer post-comment threads may offer deeper insights into emotional expressions.
- Time range: the data will be filtered based on specific timeframes, particularly around key political events or elections in Europe (e.g., national elections, EU Parliament elections). This allows for a temporal analysis of how emotions and values evolve in response to political developments.

4.2 ANONYMIZATION

Data will be anonymized as far as required. In accordance with the guidelines provided by the ethical evaluation, we will disassociate any personal information provided in the data collection. Specifically, we will replace the page and profile name (on Facebook) and the Author (on TikTok and Instagram) with a randomly generated code, or the reference code provided by the TikTok API or the Mata Content Library API.

4.3 PRE-PROCESSING

After filtering the social media data, the next step is to pre-process the text to ensure consistency and reduce noise before applying emotion and value detection models. Given the informal and often noisy nature of social media content, several specific techniques will be applied to standardize the text while preserving its emotional and contextual meaning.

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- Handling social media-specific elements: special attention will be given to platform-specific features, such as hashtags, mentions, and emojis. Hashtags, in particular, may carry emotional weight or signal value-based affiliations (e.g., #JusticeForAll, #NoToCorruption), and will be addressed as relevant labels.
- Noise removal: irrelevant elements such as URLs, repeated characters (e.g., "loooove"), and non-standard spellings will be standardized or removed unless they are integral to emotional or affective expressions. Emojis, which can convey emotion, will either be translated into text equivalents or retained for emotion detection.
- Lowercasing and punctuation: the text will be converted to lowercase for consistency. However, punctuation marks that may indicate emotion (e.g., exclamation marks or question marks) will be retained.
- Tokenization: the text will be tokenized into words or sub-words using transformer-based tokenizers compatible with LLMs (e.g., BERT tokenizers). Since social media language often includes abbreviations, slang, and emoticons, these will be carefully handled to preserve meaning. Furthermore, tokenization is a key element in the transformer process as BERT uses BPE (Byte- Pair Encoding to shrink its vocab size), so words like run and running will ultimately be decoded to run + ##ing. So it's better not to use stemming or lemmatization that will convert *running* into *run* because in some NLP tasks using transformers like BERT that information will be needed.

The pre-processing steps will be adapted to the specificities of each language, as expressions of emotion and values can differ significantly across languages. Language-specific tokenization and normalization processes will be used.

4.4 EMOTION AND AFFECTS DETECTION

Emotions and affects are the cornerstone of the ENCODE project and in this social media analysis, the proper automatic tagging of emotions and affects in the social media posts is key in articulating a comprehensive and robust analysis. We will leverage a transformer-based LLM for this purpose, which will either be fine-tuned on an emotion-annotated corpus (Scenario 1) or rely on pre-existing models (Scenario 2) if manual annotation to fine-tune the transformer is not feasible due to technical constraints by the social media data use policies for research.

4.4.1 SCENARIO 1 - FINE-TUNING THE TRANSFORMER

The LLM transformer will be fine-tuned using a manually annotated corpus of social media posts labelled with emotional and affective categories (e.g., anger, fear, joy, hope). This corpus will be generated from a random sample from the search query results and annotated by the partners of the ENCODE project.

- Creation of the non-annotated corpus: a randomly sampled set of social media posts from the query (see Section 3) will form the foundation of the annotated corpus. Posts will be drawn from the six target languages—Bulgarian, German, Polish, Bosnian, Macedonian, and Danish.
- Codebook development: a detailed codebook will be developed to guide the manual coding process. This codebook will establish the emotional and affective categories to be labelled and provide instructions for how to detect and annotate these emotions and affects across different languages and cultural contexts. Annotators will be trained on a common framework to ensure cross-language consistency.

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  - Emotional categories: the codebook will define emotional categories, with examples and guidelines for how to recognize these emotions in the political and social media contexts of each language.
- Manual coding process: The manual coding will follow a structured workflow to ensure accuracy and consistency. Each post will be manually coded for a range of emotional and affective categories such as anger, fear, joy, sadness, hope, and indignation. This manual coding will be conducted by ENCODE partners with linguistic and cultural knowledge of each of the countries/languages under study, ensuring high-quality, contextually relevant annotations. The process will begin with a pilot phase, where annotators will apply the codebook to a subset of posts to calibrate their understanding of the emotional categories. Each post will be manually labelled, with provisions for multi-label classification to account for posts that express multiple emotions or affects simultaneously.
  - Cross-cultural considerations: to account for linguistic and cultural diversity, the partners' insights on their country singularities will be leveraged to discern those nuances and address how emotions are expressed differently in each language.
  - Pilot phase: the initial pilot phase will involve coding a sample of posts from each of the six languages by multiple annotators. This phase will help refine the annotation guidelines and ensure consistent application of the emotional categories across languages. The inter-annotator agreement will be measured using Krippendorff's alpha which will be calculated using the double-coded data to assess reliability.
  - Ongoing refinement and quality control: throughout the manual coding process, periodic reviews will be conducted to ensure consistent application of the emotional categories across languages.

- Fine-tuning the transformer: after the manual coding is completed and the annotated corpus finalized, the LLM transformer will be fine-tuned using this multilingual data. The fine-tuning process will involve training the model to detect emotions and affects across the six target languages based on the manually labelled examples.
  - Multilingual fine-tuning: a multilingual transformer architecture (e.g., mBERT, XLM-R) will be used to handle posts in Bulgarian, German, Polish, Bosnian, Macedonian, and Danish. The model will be adapted to handle multi-label classification, as posts often contain multiple emotional and affective expressions.
  - Emphasis on Cross-Language Generalization: while the model will be fine-tuned for each language individually, a key goal will be to enable cross-lingual generalization. This ensures that the model can transfer insights about emotional patterns learned from one language (e.g., German) to other languages (e.g., Polish or Macedonian), improving the robustness and flexibility of the model.

- Evaluation: the fine-tuned model will be evaluated on several key metrics, including ROC AUC, precision, recall, F1-score, and accuracy, with separate evaluations for each of the six languages. The performance of the model in handling multi-label classification and detecting emotions and affects across languages will be closely monitored. The evaluation phase will also examine the model's ability to generalize emotional patterns between languages while preserving language-specific nuances. If it fails to do so, six independent models will be fined tuned to be language-specific.

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4.4.2 SCENARIO 2 – USING TRANSLATION AND ALREADY FINE-TUNED MODELS

In this scenario, we will employ machine translation to convert social media posts from the six target languages—Bulgarian, German, Polish, Bosnian, Macedonian, and Danish—into English. This will enable the use of pre-existing fine-tuned models, such as GoEmotions, which is specifically designed for emotion detection in English text. This approach allows for effective emotion analysis while minimizing the need for extensive manual annotation in multiple languages.

- Machine translation of social media posts: social media posts written in Bulgarian, German, Polish, Bosnian, Macedonian, and Danish will be translated into English using high-quality validated machine translation systems. Several machine translations will be tested per language to optimize the predictive accuracy of the pre-trained models used in the next step.

- Selection of a pre-trained and fine-tuned model: there are several models like GoEmotions, a transformer-based model fine-tuned for emotion classification, as the primary model for detecting emotions in the translated texts. These models are capable of identifying a range of emotional categories relevant to social media discourse. The translated English posts will then be processed through the transformer model for emotion and affect classification. We will make sure the chosen model supports multi-label classification, allowing the model to assign multiple emotional labels to posts that express complex or mixed emotions. We will also pay close attention to the metrics of the model ensuring the best of the performances possible as that is the reason to rely on English translation, as no models are available for such specific tasks for the six languages under study.

- Evaluation and cross-language performance: the effectiveness of this scenario will be evaluated using performance metrics such as precision, recall, F1-score, and accuracy. We will specifically focus on how well the transformer model performs in capturing emotions across the translated posts from different languages. The performance analysis will also include an assessment of the model's ability to generalize emotional detection across different linguistic and cultural contexts.

4.5VALUES DETECTION

The process for the values detection is the same as for the emotion and affect detection explained in Section 4.4. A different model will be fine-tuned for this proposed using the same annotated corpus, which will also include the classification of the values considered of interest for this analysis. These values will be detailed in the codebook and will follow the same approach as for the emotions and effects under Scenario 1 (Section 4.4.1). If such a scenario is not possible (Section 4.4.2) we can use fine-tuned BERT models like schwartz-values-classifier, that enable the classification the posts according to the Schwartz values.

Funded by the European Union
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5. QUANTITATIVE ANALYSIS

The quantitative analysis of the social media posts gathered and classified will focus on addressing the core research questions described in Section 2: (1) What role do emotions play in the online discourse in relation to the values and identity of the user?, (2) What emotions and values are conveyed in untrustworthy news compared to other news in social media?, and (3) Which affects and emotions are most triggering in terms of generating responses and reactions in social media? To answer these questions, our methodological framework outlines various statistical techniques, to draw insights from both aggregated data and individual post-level analyses. The aim is to explore how emotions and values are expressed in political debates, particularly on social media, and how these emotional expressions interact with factors such as user identity, news trustworthiness, and engagement levels. We will start by performing a comparison between the aggregate data to test the research questions (Section 5.1), to then move to more advanced techniques to evaluate the statistical relevance of results (Section 5.2) and performing regression analysis to discern further tendencies and correlations (Section 5.3). Finally, we elaborate on other techniques that can be potently used to evaluate time evolution or groping of emotions (Section 5.4).

5.1 COMPARISONS TO TEST HYPOTHESES

Comparative analysis will be crucial in testing our hypotheses related to each research question. For the first research question, we will compare the emotional content of social media posts to the values and identity markers of users. By analysing emotional expressions among different value clusters (e.g., nationalism, solidarity, or liberty) and political identity (e.g., socialist, conservative, liberal) we aim to identify patterns in how emotions align with user values and political identities. For instance, we will examine whether nationalist users express more intense emotions like anger, while those identified with solidarity tend to express hope or compassion.

The second research question will involve comparing the emotional and value content between trustworthy media posts and untrustworthy media posts. We hypothesize that untrustworthy media may evoke more extreme emotions, such as fear, outrage, or mistrust, while trustworthy media may exhibit more balanced emotional tones. This comparison will provide insights into how untrustworthy news manipulates emotions in online discourse.

To address the third research question, we will analyse which emotions are most triggering in generating user engagement (e.g., likes, shares, comments). By comparing posts with high levels of engagement to those with lower engagement, we will identify whether emotions like anger or fear drive stronger reactions compared to emotions like joy or hope. Furthermore, we will analyse the emotions represented in the comments of such posts and compare how the emotions expressed in them compare across the emotions expressed in the original posts, trying to determine if emotions are replicated, for example, if anger posts have predominantly anger comments or if on the contrary, they have comments expressing joy or hope.

Funded by the European Union

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5.2 STATISTICAL TESTS

To statistically validate our findings, a range of hypothesis testing methods will be applied. T-tests will be used for pairwise comparisons, allowing us to assess whether significant differences exist in emotional intensity or frequency between two groups, such as trustworthy and untrustworthy media posts. Additionally, Chi-Square tests will be employed to assess associations between categorical variables, such as the relationship between emotional and affective categories and specific types of news (trustworthy vs. untrustworthy) or between emotions and affects and user responses/engagement (e.g., likes, shares, comments). Finally, correlation analysis, using a correlation matrix and dendrogram structure for grouping correlated variables, will help to measure the strength and direction of associations between emotional and affective expressions and values, providing insight into which emotional expressions are correlated among each other and with certain values.

5.3 REGRESSION ANALYSIS

Regression analysis will play a key role in identifying and quantifying relationships between emotions, values, and engagement on social media. Multiple linear regression will be used to analyse how different factors such as user values, or specific emotions, describe social media engagement or political identity. We will model how emotions like anger or fear influence the number of likes or shares a post receives, addressing the third research question.

$$Engagement = \alpha_0 + \beta_1 \cdot Emotion_1 + \cdots + \beta_N \cdot Emotion_N = \alpha_0 + \sum_{i=1}^{N} \beta_i \cdot Emotion_i$$

Further interacted analysis between emotions and values will be used to understand further how different value and emotion pairs affect the diffusion and interaction of the posts.

$$Engagement = \alpha_0 + \sum_{i=1}^{N} \beta_i \cdot Emotion_i \cdot \sum_{j=1}^{M} \gamma_j \cdot Value_j$$

Similarly, we will try to discern which are the most common emotions used by each political identity group and study their differences and associated values, further elaborating on the findings regarding the first research question.

$$Political\ identity = \alpha_0 + \sum_{i=1}^{N} \beta_i \cdot Emotion_i$$

$$Political\ identity = \alpha_0 + \sum_{i=1}^{N} \beta_i \cdot Emotion_i \cdot \sum_{j=1}^{M} \gamma_j \cdot Value_j$$

In addition, logistic regression will be applied to predict binary outcomes, such as whether a post is classified as untrustworthy or trustworthy news, based on its emotional content. This will be useful in answering the second research question by examining whether certain emotions predict the likelihood of a post being untrustworthy news.

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$$P(Untrustworthy\ news) = \frac{e^{\alpha_0 + \sum_{i=1}^{N} \beta_i \cdot Emotion_i}}{1 + e^{\alpha_0 + \sum_{i=1}^{N} \beta_i \cdot Emotion_i}}$$

5.4 OTHER TECHNIQUES

There are other sets of techniques we can potentially employ to gain further insights into the data, validate our findings and gain a more nuanced understanding of emotional dynamics in social media discourse. We can utilise sentiment trajectory analysis to track how emotional expressions shift over time, particularly during key political events, providing insights into how emotions evolve over time, if the study sample allows for such type of analysis. Factor analysis can potentially be used to identify underlying patterns in the data by reducing the complexity of the emotions and values present in social media posts. By grouping correlated emotions and values into factors, this technique will help us understand whether certain combinations of emotions and values tend to co-occur. This technique can be used to further explore the correlation results to determine if there are common emotional or value-based dimensions that explain the variance in emotional expression across different groups or types of content.

Funded by the European Union

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6. CONCLUSIONS

The aim of this deliverable is to outline the methodological guidelines for conducting the work in WP3 - Analysing Social Media Communication. The goal of this research is to examine the interplay of emotions, values, and identities in political discussions on social media. Initially, we provided a theoretical framework to understand these concepts, followed by a review of empirical studies utilizing social media data. Thereafter, we outlined the research questions and scope of ENCODE. Subsequently, we define our units of analysis, focusing on the different social media platforms used for data collection, including their characteristics, content, demographic reach, and data extraction methods. In this process, we determine the information available for analysis, establish the units of analysis on each platform, and describe the iterative process of refining our search strategy to ensure high-quality data collection. Following this, we outline how we aim to use automated methods for large-scale textual data analysis to explore the role of emotions and values in political debates across Europe. We employ transformer-based LLMs either fine-tuned with a manually annotated corpus or using pre-existing models where necessary. Our methodological framework includes data filtering, anonymization, preprocessing, and the classification of emotions, affects, and values. Finally, we provide some general ways of how to conduct the quantitative analysis to answer the research questions through various statistical techniques, analysing both aggregated data and individual social media posts. We explore how emotions and values are expressed in political debates, their interaction with user identity, news trustworthiness, and engagement. We use regression analysis to assess statistical significance and examine correlations, while also exploring additional techniques for evaluating time trends and emotional groupings.

Funded by the European Union

This project has received funding from the European Union under the Horizon Europe Research & Innovation Programme (Grant Agreement no. 101132698 ENCODE).

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Funded by the European Union

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ACRONYM	FULL NAME
D3.2	Deliverable 3.2
WP	Work Package
NLP	Natural Language Processing
AI	Artificial Intelligence
LIWC	Linguistic Inquiry and Word Count Description of Action
SVM	Support Vector Machine Scientific and Quality Manager
LLM	Large Language Model
API	Application Programming Interface
VPN	Virtual Private Network
URL	Uniform Resource Locator
FYP	For You Page
ID	Identifier
ROC AUC	Receiver Operating Characteristic Area Under the Curve
ISO	International Organization for Standardization
BERT	Bidirectional Encoder Representations from Transformers

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ENCODE

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