

Cultural Memory from Antagonism to Deliberation in (Social) Media: AI Approach

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Abstract

Cultural memory refers to the shared pool of knowledge, traditions, and collective experiences that are passed down through generations within a community or society. It shapes a group's identity, provides a sense of continuity across generations, and ensures socio-political stability. However, when memories of significant historical events are contested or divisive, they can fuel antagonism and polarization within or between communities. In this paper, we present a comprehensive computational approach for measuring and analyzing social media's impact on the transformation of cultural memory.

To investigate how commemorative narratives are being transformed due to social media, we developed a large language model (LLM)-supported framework, theoretically anchored in the deliberative democracy. To identify narratives associated with specific commemorations, we use Greimas' structuralist actantial model, an analytical tool for understanding the roles and relationships between narrative functions (actants) in discourse. Computationally extracted narrative actants are cross-analyzed on a scale of antagonism, agonism, and deliberation and evaluated within a discourse functions analysis (epistemic, ethical, democratic, and ideological), adapted from the deliberative democracy theoretical framework.

The approach is first human-evaluated to check validity of automated extractions and then demonstrated using social media and newspaper articles about the Slovenia's commemoration of the Day of Resistance against Occupier as a case study. The results provide precise insights into how different segments of the narrative in social and traditional media reinforce antagonism, foster agonistic debate, or create opportunities for deliberation. Special attention is given to identifying points of conflict and establishing common ground through computational analysis. We underscore the methodological novelties leading to broader applicability of the demonstrated approaches, emphasizing their potential to develop an automated pipeline for analyzing debates on divisive collective memories in different contexts, as well as for assessing the quality of other types of discourse.

Keywords: social media, cultural memory, deliberative democracy, Greimas actant model, large language models (LLMs), prompt engineering, statistical analysis, political discourse

1. Introduction

Cultural memory provides a shared set of historical markers or sites of memory (*les lieux de mémoire*, Nora 1984) to which communities refer in establishing their collective identity (Assmann and Czaplicka 1995). These reference points of memory can include monuments, commemorations, pivotal or divisive historical events, rituals, but also collective traumas, such as the Holocaust (Winter 2008). As such, cultural memory plays a multifaced role in public discourse. It can be integrative, as it helps stabilize public discourse, particularly in nation-building processes (Anderson 1983; Hobsbawm 1983). However, these processes are not inherently neutral; they often involve contested narratives, exclusions, and ideological struggles over historical interpretation. Differing perspectives, shaped by ideological or political orientations as well as personal and collective experiences, can lead to conflicting interpretations of historical events (Rothberg 2009). These conflicts can perpetuate social divisions and political polarization (Tveskov and Bissonnette 2023), particularly when politically instrumentalized by populist and nationalist governments (Wodak & Richardson 2013). “Memory wars” are not limited to the re-interpretations of 20th century history. They fuel modern conflicts, as evidenced by the role of cultural memory in contemporary geopolitical tensions (Rutten et al. 2013; Pshenychnykh et al. 2024).

Studies show that **digital technologies profoundly transform cultural memory** (van Dijck 2007). The mediatization of memory has led to a “connective turn” in which private and public spaces intertwine, and memory is continuously constructed and reconstructed through digital interactions (Hoskins 2011). Memory is thus no longer shaped by state institutions, museums, and traditional media but is increasingly influenced "from below," by grassroots movement, challenging official narratives and prompting new interpretations. Online platforms have facilitated hashtag-based memory activism (Gutman and Wüstenberg 2023), allowing people across different locations to “forge mnemonic communities for the sake of promoting a certain memorialization agenda” (Yasseri et al. 2022, 9). This can be noted in online discussions following armed conflicts, as in the case of the wars in the Western Balkan in the 1990s (Labonté 2024; Fridman 2022). Hashtag activism can involve the revival of historically problematic ideologies, as evidenced in Germany by the AfD use of social media (Richardson-Little et al. 2022) but it can also support calls for redress for historically marginalized groups (counter-memory), as seen in movements like #BlackLivesMatter (Ruiz 2024).

This **transformation of cultural memories has a direct impact on democratic stability** (Mitzal 2005; Meyer 2008; Wüstenberg 2023; Verovšek 2021). To explore this transformation in relation to democratic standards, this paper introduces a comprehensive theory- and LLM-supported research framework designed to measure and analyze the impact of social media on shared and contested memories. Specifically, it examines changes in commemorative narrative structures and discourse quality. We argue that providing systematic insights into shifts in cultural memory - now for the first time accessible through a large-scale semantic and socio-semiotic data analysis - is a prerequisite for maintaining political stability and effectively addressing the underlying causes of democratic backsliding.

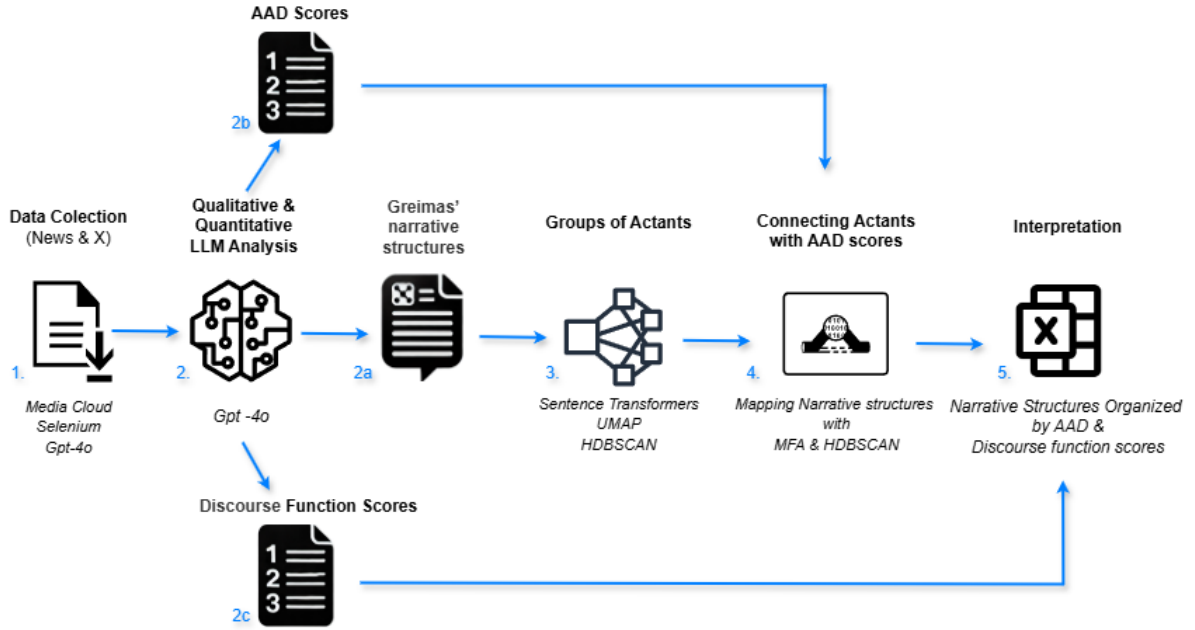


Figure 1: The methodological pipeline is split into several interconnected steps, further elaborated in Section 3. Following the data collection (1), the semantic analysis of various narrative structures was conducted using GPT-4o. The LLM-based methodology (2) included three distinct but interrelated analyses. First, a Greimas' actantial narrative analysis (2a) was conducted to extract six fundamental actantial roles, alongside their ideological classification as left, centre, or right. Second, an antagonism–agonism–deliberation (AAD) analysis (2b) assessed the rhetorical structure of the texts by classifying them as antagonistic, agonistic, or deliberative. Third, a discourse functions analysis (2c) framework evaluated texts along five dimensions - epistemic, ethical, ideological, and democratic - each scored on a 0–100 scale to infer the underlying motivation of the text. To refine the Greimas' narrative structures, we grouped actant roles with clustering, using contextual embeddings as text representation (3). Actants were converted into high-dimensional vector representations using a SentenceTransformer model. Their dimensionality was then reduced via UMAP, and hierarchical density-based clustering (HDBSCAN) was used to cluster actants with similar semantic properties, thus consolidating the actants. Finally, Exploratory Multiple Factor Analysis (4) was conducted to uncover relationships between actantial narrative structure and AAD scores. This analysis structured actantial narrative formations by their corresponding AAD scores, with hierarchical density-based clustering applied to detect recurring patterns in our datasets. The final step of our methodology involved human interpretation, using the results of previous steps to highlight salient patterns.

To evaluate how social media transforms public discourse in terms of narrative structures and deliberative shifts, we applied the same methodological approach to posts on social media and traditional media. Based on this methodology, which was first human-evaluated, we tested the following hypotheses:

H1: Narrative Transformation: social media creates an environment where cultural memory becomes more personalized, fragmented, and susceptible to distortion, compared to the more institutionally anchored and stabilized narratives in traditional media.

H2: Transformed Deliberative Practices: social media increases the presence of agonistic and antagonistic engagements, altering narrative dynamics compared to traditional media, where more structured and less dynamic discussions on historical events tend to dominate.

H3: Cultural Memory and the Public Sphere: Transformations of cultural memory on social media undermine epistemic authority over historical narratives, affecting the stability of the public sphere.

To validate **H1**, we investigated whether social media platforms facilitate a shift from collective to individualized memory construction, leading to more fragmented, contested, and fluid historical interpretations. The *key indicators* include a) actantial cluster count – the number of distinct narrative structures, derived from the narrative analysis of traditional and social media; b) fragmentation level – operationalized as the variance in cluster size and the number of sub-themes per major narrative; structural coherence – assessed through the relationships between individual actants within narrative structures.

To validate **H2**, we examined the extent to which social media influences the agonistic, antagonistic, and deliberative dimensions of debates on cultural memory. Additionally, we explored whether social media creates new agonistic and deliberative opportunities that are less prevalent in traditional media. The *key indicator* is the categorization and comparison of narrative structures based on AAD scores across social and traditional media.

To investigate **H3**, we analyzed how social media-driven changes in cultural memory impact the epistemic, ethical, democratic, and ideological dimensions of public discourse. Furthermore, we assessed the implications of these changes for democratic stability and the resilience of public deliberation. The *key indicator* is the difference in mean epistemic function scores between traditional and social media.

The primary aim of our research is to systematically analyze the relationship between narrative functions (i.e., actants), AAD scores, and discourse functions to **pinpoint areas of conflict** and **identify opportunities for consensus-building** through computational analysis.

We developed and empirically validated our approach using the politically contentious **Slovenian commemoration of the Day of Resistance Against the Occupiers** (April 27, a national holiday) as a case study. This commemoration revolves around the contested memory of the founding of the Liberation Front in April 1941, the role of the Partisan resistance movement in World War II, its relation to the communist revolution in Slovenia/Yugoslavia, and the broader significance of anti-fascist resistance. The Day of Resistance is one of the commemorations where political-ideological narratives intersect with divisive, personalized, and collective memories, as well as historical traumas - particularly in relation to the postwar executions of wartime Nazi collaborators. Additionally, this commemoration is deeply entangled in political and ideological disputes regarding the role of the socialist regime in the postwar period (Kranjc, 2013; Prunk, 1992; Pirjevec, 1995; Godeša, 1995). More broadly, it reflects the ongoing polarization between conservative and liberal factions in Slovenian society (e.g. Hribar & Hribar, 2021)

The results reveal **significant correlations between levels of antagonism and agonism within specific narrative clusters**. Additionally, the study identifies narrative segments where

opportunities for improving deliberation emerge. Notably, some findings derived from LLM-based, large-scale data analysis appear initially counterintuitive. However, a deeper interpretative approach uncovers underlying narrative structures that shape antagonism, agonism, or deliberation on social media - **structures that often remain inaccessible to traditional discourse analysis.** The study precisely maps the points in the narrative structure where antagonisms arise, agonisms are activated, and deliberation is fostered. We argue that the applied methodology for examining both integrative and contested memories holds significant **potential for informing policy strategies** aimed at conflict mitigation. Further, the developed methodology is broadly applicable to structural analyses of texts and, for the first time, enables theoretically grounded, large-scale analyses of complex narratives in both social and traditional media.

The paper is structured as follows. Section 2 provides a necessary background and concise overview of the related theoretical and methodological literature. Section 3 outlines the methodological framework and details its implementation. Section 4 covers the evaluation of the methodology and its correlation with human annotations. Section 5 presents the results of the analysis, while Section 6 discusses the findings of the computational approach, highlights its limitations, and reflects on its broader implications. Finally, the conclusions in Section 7 summarize the key insights and propose directions for future research.

2. Theoretical background and related work

Our research integrates multiple approaches that have not yet been systematically connected. Theoretically, it introduces a novel operationalization of the relationship between cultural memory and democratic practices by employing the theoretical framework of deliberative democracy. This type of democracy is grounded in the philosophically compelling idea that the best solutions to concrete social dilemmas or problems emerge through deliberation - an inclusive, argument-based, and respectful discussion among equal individuals, aimed at ensuring the common good (Habermas 1996; Rawls 1993; Cohen 1989; Mansbridge et al. 2012). In this analysis, we expand and adapt this theoretical framework to analyze cultural memory.

For this purpose, we operationalize deliberative democracy as a tool, goal, and context (Bianchi 2008) for examining social media and traditional media discussions on cultural memory. However, given the distinct nature of these discussions - often extending beyond a reason-based framework of the deliberative democracy - we expand the framework by integrating three additional theory-driven components (see *Figure 1*), whose background and related works are presented in the following sections: i) Recognizing narratives as both a meaning-making tool and a foundational element in political opinion formation and decision-making (*Section 2.1*), ii) Extending existing measurements of deliberative quality by incorporating antagonism and agonism scores (*Section 2.2*), and iii) Identifying the underlying aims of discussions through the lens of discourse functions, thereby adapting and expanding the goals of deliberative democracy (*Section 2.3*). We also examine the current capabilities of LLMs for analyzing large-scale datasets relevant to our work (*Section 2.4*). Based on the three extensions

presented in Sections 2.1 to 2.3, we developed three methodological components presented in *Section 3*.

Overall, the presented extensions redirect our analysis from a predominantly procedural conception of deliberative democracy - where discourse quality is assessed through quantitative measures such as the Deliberative Quality Index (DQI) - to a summative approach (Bächtiger & Parkinson 2019), which focuses on deliberative outcomes and recognizes that deliberative results can emerge even through non-deliberative components, such as online platforms (Stolwijk et al., 2023, p. 6).

Our approach aligns with the LLM-based capability of analyzing large-scale data. As we show, unlike conventional computational methods, LLMs enable a comparative analysis of various contextual factors influencing opinion formation and political attitudes through the lens of discursive quality. Specifically, this method facilitates the analysis of narrative structures, AAD scores, and discourse function ratings, enabling us to systematically assess how different discussion modes interact within commemorative debates and evaluate them at a summative level. By doing so, our research pioneers the integration of state-of-the-art LLMs and other machine-learning tools into the study of complex societal issues, particularly the dynamic interplay between cultural memory, democratic practices, and social media.

In the remainder of this section, we outline the background and related works that inform the main components of our methodology.

2.1. Narrative Analysis: Greimas' Actantial Model

Algirdas Julien Greimas, drawing on Lévi-Strauss's structural analysis of myth ([1955] 1963) and Propp's morphology of tales ([1928] 1968), developed a structural linguistic framework known as narrative semiotics. His model is designed to analyze the roles, functions, actions, and modalities within narratives. This model (Greimas, [1966] 1983) has been applied to wide range of texts, including legal discourse (Jiang 2017), media narratives (Aarva, 2006; Langer 2000; Hartz and Steger 2010; Bacallao 2010), fairy tales (Wenno, Serpara and Litualy 2021), film analysis (Hu et al. 2024), visual grammar (e.g., Salama, 2021), and self-narratives related to identity construction, for instance by Wang and Roberts (2005) in the analysis of identity-formation in China's cultural revolution (1966–1976).

To illustrate this model, we use J.R.R. Tolkien's novel *The Lord of the Rings* as an example (*Figure 2* illustrates axes or relationships).

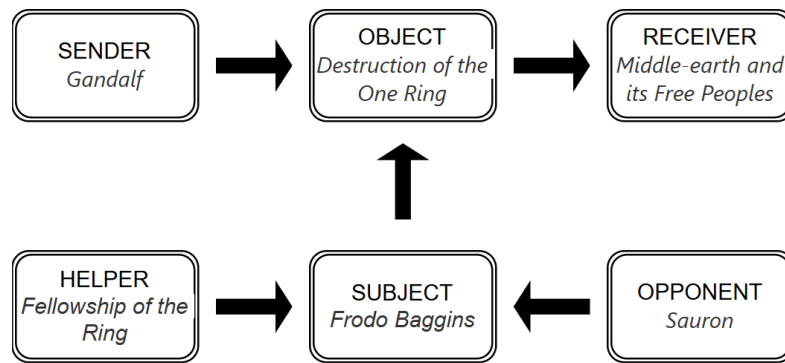


Figure 2: The illustration of the Greimas' actantial model showing the narrative structure of *The Lord of the Rings* novel.

(1) **Axis of quest** – the subject-object (such as *Frodo Baggins* in *The Lord of the Rings*) strives to achieve a specific object – goal (*destroying the One Ring in Mount Doom – the evil Sauron*).
 (2) **Axis of communication** – the sender-receiver relation, in which the sender (*Gandalf, representing the struggle for freedom and the preservation of Middle-earth*) sends the subject on a narrative trajectory for the benefit of the receiver (*Middle-earth and its free peoples*); which explains the motivation or reason behind the narrative trajectory – identifying what drives the subject to act and for whose benefit.
 (3) **Axis of conflict** – the helper-opponent relation, which highlights the forces aiding or opposing the subject's progress along the narrative trajectory, distinguishing those who support the subject (*Samwise Gamgee, the Fellowship of the Ring*) from those who obstruct it (*Sauron, the Ringwraiths, Gollum, and various enemies along the way*).

This model can be used to analyze the historically grounded narrative of our case study - the Slovenian Day of Resistance – as illustrated in *Figure 3*. Here, the Liberation Front and Partisan movement (subject) are positioned as the principal historical actors in achieving the liberation of Slovenia from fascist occupation (object). This struggle is framed as foundational to Slovenian national identity, with the Partisan resistance credited for securing national sovereignty, democracy, and antifascist values. However, in contemporary political discourse on commemoration, the subject of the discourse depends on the political perspective. For left-wing and liberal political actors, the Partisans and the Liberation Front act as the central figures of resistance. For right-wing and conservative actors, the notion of national resistance can be broader, including non-communist anti-fascist groups or even “Domobranci” - collaborators of the occupying forces and victims of post-war executions.

Discourse-based political analysis of the Resistance Day commemoration typically identifies two fundamentally antagonistic and mutually exclusive contemporary narratives. However, our preliminary research reveals that, despite their ideological charge, discussions in both traditional and online media are more nuanced and multifaceted than this binary suggests. Many news articles and X posts cannot be neatly classified within either narrative. Furthermore, any analysis grounded in a priori antagonism merely reflects its defining features but fails to provide deeper insights into the narrative structure or potential pathways for transcending these divisions - whether through conflict mitigation or by incorporating agonistic or deliberative elements into the discourse (see *Section 2.2*). Recent deliberative democracy

theory namely highlights the potentials and role of “discursive bridges” in mitigating ideological polarization (Bächtiger & Dryzek 2024).

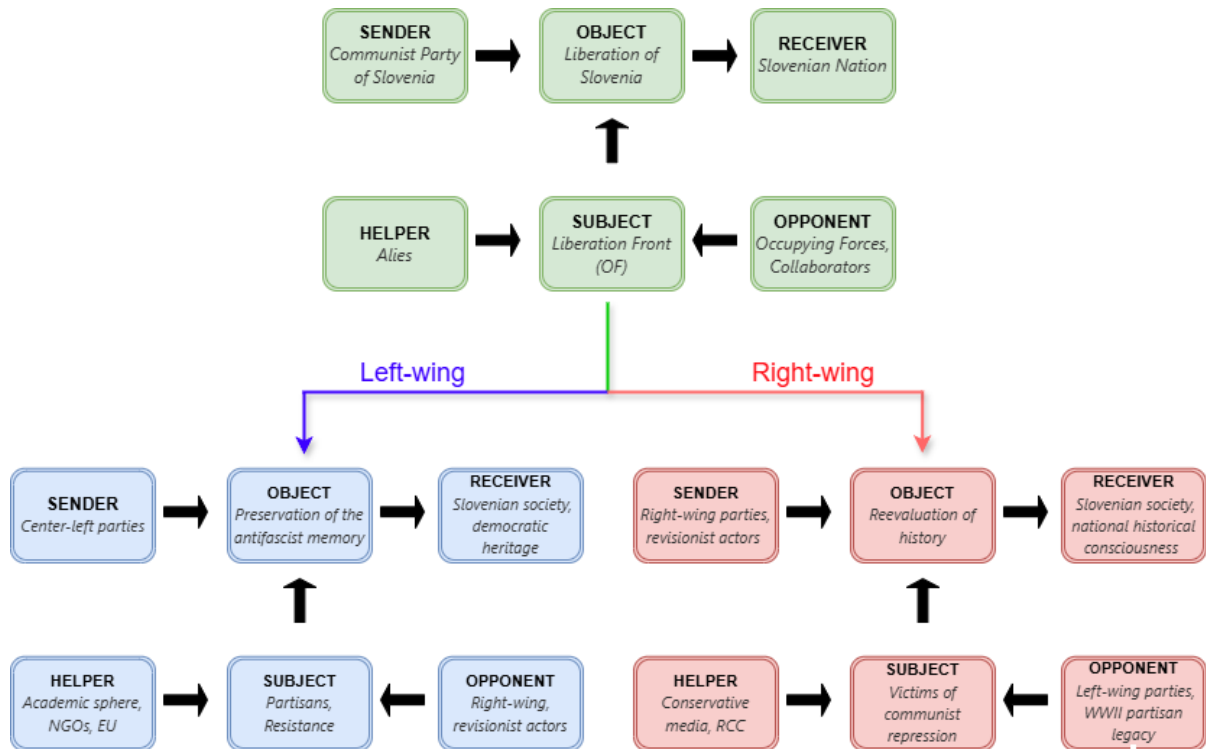


Figure 3: Historical and contemporary narrative structures of Slovene Day of Resistance.

The research suggests that AI-supported tools can enhance the structural analysis of narratives, providing greater depth and nuance. In recent years Greimas structuralism and actantial model has been used in the analysis of media and social media discourse, with special emphasis on various themes such as construction of political enemy (Teodorescu and Drăgan 2022), hate speech (Römer-Pieretti, Said-Hung, and Montero-Díaz 2025), populism (Schoor 2021) and media discourse on migrations (Hernandez, Greco, and Drzewiecka 2023). However, only with the recent rise of GenAI and LLMs (Generative Artificial Intelligence and Large Language Models) has the actantial model been more frequently (although with still only a few research conducted) explicitly used for computational analysis of large text datasets, particularly in social media discourse (e.g., Tangherlini et al., 2020; Willaert, 2023) and political media analysis (e.g., Elfes, 2024).

Our approach diverges from previous computational applications of the actantial model by prioritizing discourse-linguistic analysis over sentence-level approaches. We emphasize distinctions across three structural levels of the actantial model – deep-narrative, narrative-discursive, and figurative-discursive – and more explicitly differentiate *actants* (as abstract structural functions shaping narrative organization), *actors* (as mediators actualizing the actants) and *characters* (as figurative entities within textual discourse) than earlier LLM-based studies. Previous computational studies have primarily identified either deep-structural actants or surface-level characters, often overlooking the intermediary actorial dimension, which significantly informs overall structure (e.g., Elfes, 2024; Tangherlini et al., 2020).

At the core of our research is an exploration of how actantial configurations interact with cultural and communicative memory frameworks across media, advancing a semiotic rather than purely linguistic approach to communication (cf. Cooren, 2008). Our LLM-assisted Greimasian analysis extends this perspective by introducing *semiotic inference* and *narrative structure inference* – the implicit identification of deep-narrative functions and structures beyond surface syntax and figurative discourse. Each actant is inferred through the semantic and syntactic elements that occupy its position and their relationships to other elements in the narrative. At the same time, this inference is shaped by the broader structural relations within the narrative (by other actants) and the context in which the text is articulated. In other words, actantial meaning is constructed not only through individual linguistic units and their immediate connections but also through the way these elements interact within the overall discursive framework of the text. This focus on abstract narrative functions rather than solely on fixed, manifested entities, enables a systematic study of how meaning is constructed within discourse. Our methodology refines this by clearly distinguishing the three structural layers, a crucial step for enhancing LLM prompt engineering and enabling more precise, large-scale actantial analysis.

2.2. Antagonism, agonism in deliberation in cultural memory research

From a political discourse perspective, cultural memory - particularly on social media - can be analyzed through three theoretical lenses: antagonism, agonism, and deliberation.

Antagonism aligns with research on toxic polarization driven by homophily (McPherson et al. 2001), filter bubbles (Pariser 2011), and echo chambers (Cinelli et al. 2020). It manifests as affective polarization, where opposing groups refuse to recognize each other's legitimacy (Törnberg 2022). This is evident in commemorations framed as "our truth" vs. "their lies", such as the Slovenian Day of Resistance or the European Day of Remembrance for Victims of Totalitarianism. More issue-driven commemorations, like Europe Day, tend to allow substantive debate rather than rigid ideological opposition.

Agonism differentiates between enemies (antagonism) and adversaries (agonism), while the key democratic challenge is to "transform antagonism into agonism" (Mouffe 2002, p. 755). In memory studies, this perspective has been employed in analyses of divided or contested memories, where deliberative theorists, following Aleida Assmann, emphasize the importance of mediating memory through rational discourse to foster consensus and mutual understanding. Agonistic theorists, drawing on Mouffe, reject the idea that memory debates can ever be purely rational, or consensus driven. Instead, they argue that imposing a singular, consensual narrative may contribute to political exclusion and fuel populist backlash. Victim-centered narratives, for example, can marginalize alternative perspectives, leading them to resurface in more extreme forms (Nienass, 2023). Outside memory studies, some recent computational research has utilized this distinction. Canute et al. (2023) developed an annotation schema to classify conflict dimensions - sources, targets, and rhetorical strategies - using machine learning to distinguish agonistic debates from antagonistic discourse. However, this distinction remains implicit in their model. Potts et al. (2024) introduced the Online Conversion Framework, an eight-level scale mapping how antagonistic interactions shift toward agonism on social media.

While theoretically insightful, the model is primarily designed for policymakers and platform designers

The third lens views deliberation as a mechanism for reducing antagonism and polarization, either at the systemic level (Mansbridge & Parkinson 2012) or by employing deliberative discourse to explore tensions in historical, interethnic, and memory conflicts (e.g. O'Flynn, 2006). This approach has been utilized to explore digital deliberation, e.g. the Deliberative Quality Index (DQI) (Steenbergen et al. 2003) and its updated DQI2 (Bächtiger et al. 2010) to assess deliberative quality (Beauchamp 2020; Fournier-Tombs & MacKenzie 2021; Oswald 2022). These indicators have also shaped the development of digital democratic innovations (Mikhaylovskaya 2024; Shortall et al. 2022). Increasingly, research explores the role of AI as a tool for facilitating online deliberation (McKinney 2024; Landemore 2024).

The need for a systematic analytical approach to assess commemorative debates across antagonism, agonism and deliberation is becoming increasingly evident. In our research, antagonism corresponds to toxic polarization, where discussions are dominated by irreconcilable conflicts, and opposing actors refuse to acknowledge each other's legitimacy. Agonism represents constructive contestation, where disagreements are openly expressed within a structured framework that maintains political engagement and prevents discourse from descending into hostility. Deliberation, in turn, functions as discursive mode that facilitates the transformation of conflicts into reasoned debate and fosters a new *modus operandi* for historical reflection and collective memory negotiation.

Although all three of these discursive dimensions - antagonism, agonism, and deliberation - have been studied in social media contexts, to the best of our knowledge, there has been no attempt to systematically measure and compare all three components within online discourse, particularly in the context of discussions about cultural memory, and by using LLM-based tools. By applying LLM-supported narrative analysis, this study quantifies and evaluates the interplay between these three discursive modes in commemorative debates, offering novel insights into the shifting role of cultural memory in democratic societies.

2.3. Discursive functions and cultural memory

Given the complexity of discussions on cultural memory, it is crucial to distinguish and identify the various functions or objectives embedded in commemorative discourse. These discussions encompass multiple dimensions, for example, some users emphasize historical facts, others advocate democratic principles, some invoke the right to personal memory, while others embed ideological undertones that reinforce a particular narrative.

These aspects must be considered when evaluating discourse quality in terms of specific characteristics and underlying structure of commemoration. For instance, certain commemorations are inherently ideologically charged, while in some deeply divided societies, "a gentle style of communication is itself a message - what matters most is how people engage with one another, rather than the sophistication of their arguments" (Habermas, 1996, p. 26). To systematically assess the structure of commemorative discussions, we apply the deliberative

democracy framework outlined by Mansbridge et al. (2012), which distinguishes three key deliberative democracy functions.

The epistemic function asserts that deliberation should contribute to better decision-making by ensuring that arguments are based on scientific, verifiable, and logically coherent information. In the context of cultural memory, a consensus on historical facts is a prerequisite for meaningful discussion. When epistemic integrity is undermined, discussions risk being based on false premises, such as conspiracy theories; for example, narratives that deny the role of collaborationist regimes in World War II.

The ethical function emphasizes that deliberation must be grounded in mutual respect. Even when participants disagree, they must recognize each other as legitimate discussion partners. In cultural memory debates, this principle extends to the right to interpretation and remembrance, but also to broader concepts of restorative justice (Mitzal, 2005). However, as Amy Wüstenberg (2023) stresses, not all historical memories are inherently democratic. Some commemorate figures or events associated with authoritarianism, nationalism, or repression, raising questions about how these memories should be contextualized within democratic norms.

The democratic function refers to the equal inclusion of all voices in deliberation. For example, the European Day of Remembrance for All Victims of Totalitarianism is often framed through a democratic lens, invoking universal human rights and anti-totalitarianism. However, it has also been used to promote exclusionary narratives, equating all historical experiences of repression without contextual differentiation (see e.g. Kopeček, 2008).

Finally, as discussions on cultural memory are often politically driven, with the primary objective being the dominance of a specific narrative, it is crucial to differentiate ideological motivations from epistemic, ethical, or democratic considerations. For this reason, we have expanded Mansbridge et al. (2012) framework by incorporating an *ideological function*, allowing for a more precise distinction between deliberative and ideologically driven discourse.

These functions are not always mutually exclusive and can sometimes be in tension. The ethical right to memory can conflict with the democratic function, especially when memory claims contradict historical evidence or democratic standards. Similarly, the epistemic function may be subordinated to ideological narratives. Some nationalist commemorations selectively emphasize certain historical events while marginalizing others to reinforce a political agenda.

2.4. LLMs in social media analysis

In recent years, using computer-based methods have become increasingly popular when analyzing social media. Methods from the field of natural language processing (NLP) and computational linguistics allow for automatic analysis of large amounts of data, far exceeding what's possible with manual analysis. Traditionally, such analysis was done using specialized machine learning models which were trained on human-annotated, task-specific data and could then make predictions related to that specific task. While these approaches are useful, their

reliance on task-specific annotated data makes them unsuitable for tasks where such data is not available.

More recently, large language models (LLMs) such as GPT (Brown et al. 2020), Llama (Grattafiori et al. 2024) and DeepSeek (DeepSeek-AI et al. 2024) have become widely used for analyzing social media. Large language models make use of large amounts of training data and specialized neural network architectures and have been shown to outperform other methods in most NLP tasks (Brown et al. 2020). Due to the large amount of training data, LLMs can encode a huge amount of general-world knowledge making them especially suitable for the semantic analysis of natural language. Additionally, many such models have been trained on multiple languages, allowing them to analyze non-English texts effectively.

LMM-based analysis of social media and political discourse usually focuses on big events and popular languages, such as analyzing voter preference before US elections or determining political stance of US social media users (AlDayel and Magdi 2021; Kawintiranon and Singh 2022). Nemeth (2023) present a survey of 154 such studies and show a heavy bias towards US contexts (59%) and Twitter/X data (43%). Additionally, very few such studies are multidisciplinary, often making use of only NLP approaches, did not take domain knowledge into account, or had trouble properly interpreting results. Studies that combine expert knowledge of political and social sciences and computer-based approaches are therefore rare and represent a significant gap in related work.

Automatic analysis of cultural memories remains underexplored and is virtually nonexistent for less-resourced languages such as Slovene. To the best of our knowledge, our approach is the first to tackle this issue by combining a robust theoretical foundation with AI-based methods (i.e., LLMs, topic modelling, clustering) and statistical analysis.

3. Methodology

The focus of this study is to develop an automated, LLM-based approach for analyzing the narrative structures of cultural memories in social and traditional media, specifically in terms of deliberative quality and the underlying motivations of authors, including epistemic, ethical, democratic, and ideological considerations. As the main computational engine, we used GPT-4o, which, according to its authors, demonstrates capabilities comparable to human performance across a range of professional and academic assessments (OpenAI, 2023). *Figure 1* illustrates the complete automated methodological pipeline. The following sub-sections provide a detailed account of each methodological step outlined in *Figure 1*. The steps constituting our methodological apparatus are evaluated in *Section 4*.

Below, each component of our methodology is elaborated to provide a comprehensive explanation of the processes and computational techniques employed. Using three distinct, carefully designed prompts executed through OpenAI API, we used GPT4-o to conduct three qualitative data analyses, each grounded in the theoretical framework outlined in *Section 2*.

In *Section 3.1*, we describe automated application of Greimas's narrative analysis. In *Section 3.2*, we conduct an Antagonism – Agonism – Deliberation (AAD) analysis, and in *Section 3.3*, we develop an approach for a discourse function analysis derived from the deliberative

functions framework (Mansbridge et al. 2012). Each prompt went through various iterations of testing and tweaking to ensure that the results were as accurate and consistent as possible. In *Section 3.4*, we demonstrate how actant embeddings were clustered. In *Section 3.5*, we explain how actants were connected to AAD scores and discourse function ratings within actant structures. In *Section 3.6*, we outline other methods we tested for narrative extraction and deliberative quality measurements. In *Section 3.7*, we provide details on the data used.

3.1 Greimas narrative extraction

In this section, we explain prompt development for conducting Greimas’s actantial narrative analysis (see *Section 2.1* for its description) to analyze narratives in our two datasets of traditional and social media texts. Greimas’s model identifies six actantial roles that structure the narrative logic of a text: subject, object, sender, receiver, helper, and opponent. Each role is analyzed at three levels: actant (the abstract functional role in the narrative), actor (the entity manifesting the actant in the narrative), and character (the specific, individualized manifestation of the actor within the text).

To operationalize this analysis, we implemented a computational workflow using the GPT-4o API. The system was programmed to process each text (news article or X comment) in the dataset by applying a standardized prompt designed to identify and classify actantial roles according to three aforementioned levels (see [Appendix A](#)¹ for full prompt). In addition, we used a specialized prompt instructing GPT-4o to determine whether each actant aligned with left-wing, center, or right-wing perspectives. Drawing on the guidelines provided - ranging from progressive or anti-fascist leanings (left) to institutional or neutral stances (center) and conservative or nationalist frameworks (right) - the model assigned each actant an ideological label alongside its actantial role.

The results of the analysis were compiled into a tabular dataset. This dataset includes both the raw textual output from the language model and a structured parsing of the actantial roles, enabling further qualitative and quantitative analysis. The structured output categorizes data into fields corresponding to each actantial role and its three analytical levels (actant, actor, and character), ensuring clarity, consistency and transparency in subsequent analysis.

3.2. AAD Scores

The second analytical step in our methodology involves examining Antagonism-Agonism-Deliberation (AAD) scores (see *Section 2.2*). This analysis aimed to identify and categorize texts into three distinct discursive modes: antagonism, agonism, and deliberation. Each mode was defined by specific linguistic, rhetorical and tonal features, enabling a systematic evaluation of how these rhetorical strategies manifested in the dataset (see [Appendix B](#)² for the full prompt).

¹ <https://github.com/REFMF/Cultural-Memory-from-Antagonism-to-Deliberation-in-Social-Media-AI-Approach-/blob/main/Appendix%20A%3A%20Prompt%20Structure%20for%20Greimas%E2%80%99s%20Narrative%20Analysis>

² <https://github.com/REFMF/Cultural-Memory-from-Antagonism-to-Deliberation-in-Social-Media-AI-Approach-/blob/main/Appendix%20B%3A%20Prompt%20Structure%20for%20AAD%20Analysis>

For the news articles, the model evaluated each text by detecting and counting instances of deliberative, antagonistic, and agonistic discourse, assigning a six-point score (ranging from strong antagonism to strong deliberation). For social media, in contrast, due to the brevity of X comments, a simplified three-point scale was applied, categorizing discourse as primarily “Antagonistic,” “Agonistic,” or “Deliberative”. If no clear dominance of any category was detected or insufficient information was available, the model assigned the score “N/A”. These results were compiled into a structured tabular dataset, where each textual unit - news article or X comment - was recorded along with its assigned score and the frequency of deliberative, antagonistic, and agonistic language identified in the text.

3.3 Discourse functions ratings

The third step of the analysis is the detection of five key analytical dimensions of discourse functions: “Epistemic function,” “Ethical function,” “Ideological function,” and “Democratic function” (see *Section 2.3* for the explanation). To each text, the model assigns a 0-100 score to each dimension, indicating its relative prominence in the text (see [Appendix C](#)³ for full prompts). The Epistemic function addresses the clarity and accessibility of fact-based knowledge; the Ethical function examines fairness, justice, and moral responsibility; the Ideological function evaluates the text’s political or social influence; the Democratic function emphasizes inclusiveness, transparency, and accountability.

In *Table 1*, the results of all three analytical steps (from *Sections 3.1, 3.2, and 3.3*) are illustrated using examples from a newspaper article and an X (Twitter) post. The article was published in the right-wing weekly *Demokracija*, which challenges the official interpretation of the Day of Resistance commemoration significance. It states: *"What do we celebrate on April 27? A national epic or a tragedy? A national holiday should be something that unites us and makes us all proud. The Day of Resistance certainly does not. At this year's celebration of the 'Resistance' holiday, I listened to the speech by the President of the National Assembly, Urška Klakočovnik Zupančič, who sees no problem in the holiday, only its greatness, arguing that Slovenia could only become a democratic state this way."* The author of the below X post is the Slovenian Prime Minister Dr. Robert Golob, who writes affirmatively about the significance of this holiday: *"The Day of Resistance Against the Occupier is a holiday of remembrance and reflection."*

Table 1: Example of Greimas' output generated by ChatGPT for the Slovenian Resistance Day case study, featuring original actants with inferred political orientations (Right-Wing/RW, Center/C, Left-Wing/LW), along with AAD scores and discourse function ratings.

	<i>News Article</i>	<i>X Comment</i>
Subject	National identity discourse (RW)	Commemoration (LW)
Object	Historical narrative (RW)	National unity (LW)
Sender	Ideological beliefs (RW)	Historical memory (LW)

³ <https://github.com/REFMF/Cultural-Memory-from-Antagonism-to-Deliberation-in-Social-Media-AI-Approach-/blob/main/Appendix%20C%3A%20Prompt%20Structure%20for%20Discourse%20Function%20Analysis>

Receiver	Slovenian public (RW)	National identity (LW)
Helper	Historical revisionism (RW)	Public discourse (LW)
Opponent	Establ. historical narratives (LW)	Forgetfulness (RW)
Antagonism Score	Mild Antagonism	Deliberation
Epistemic Function	62	20
Ethical Function	65	15
Ideological Function	78	10
Democratic function	58	5

3.4 Text representation with embeddings for generalization and clustering

To compare different texts, group similar ones, and generalize the findings, we used advanced neural approaches from natural language processing (NLP). As a precondition, these methods require that texts are represented as numerical vectors, capturing their semantical properties.

For example, as described in *Section 3.1*, each text in the dataset was first annotated with actantial roles - namely, Subject, Object, Sender, Receiver, Helper, and Opponent. Many of these actants overlapped semantically, exhibiting only minor variations in naming. To capture and unify these variations, each actant string was represented as a high-dimensional vector using the SentenceTransformer model (all-mpnet-base-v2)⁴, then subjected to dimensionality reduction via UMAP (Uniform Manifold Approximation and Projection)⁵. The low-dimensional projections of all texts for a given actant were grouped using HDBSCAN (Hierarchical Density-Based Spatial Clustering of Applications with Noise) clustering algorithm to identify groups of semantically similar actants.

Our code was designed to automatically test various parameters of the dimensionality reduction technique and HDBSCAN minimum cluster size settings, searching for the optimal Silhouette scores for non-outlier points. The HDBSCAN clustering was selected because of its capacity to discover clusters of varying densities without requiring a predetermined number of clusters. Points that lacked sufficient density in the vector space were labeled as outliers.

Descriptions in each non-outlier cluster were then generalized by assigning them a concise descriptive label using GPT-4o via API. We provided the model with actant names from each cluster; in response, it generated a short (1–3 word) designation reflecting their shared semantic theme. After naming the clusters, we prompted GPT-4o again to detect and merge any clusters deemed semantically identical, thus reducing redundancy and ensuring clarity in subsequent analyses. Outliers were re-examined through a second prompt, where GPT-4o attempted to integrate them into existing clusters based on semantic alignment. Only if ten or more outliers coalesced around a distinct conceptual theme would a new cluster be created, ensuring that minor variations did not fragment the data. This consolidated dataset enabled more robust qualitative and quantitative investigations, such as conducting further statistical analysis. For illustrative purposes we present an example of a final »Opponent Actant« cluster with original actants assigned by ChatGPT-4o (see *Table 2*).

Table 2: Example cluster for Opponent Actant “Oppression & Threats”

⁴ <https://huggingface.co/sentence-transformers/all-mpnet-base-v2>

⁵ <https://github.com/lmcinnes/umap>

<i>Original Opponent Actants</i>	<i>Final Opponent Actant Cluster</i>
<i>Oppressive Forces</i>	Oppression & Threats
<i>External Aggression</i>	Oppression & Threats
<i>Historical oppression</i>	Oppression & Threats
<i>Foreign oppression</i>	Oppression & Threats
<i>Modern societal threats</i>	Oppression & Threats
<i>Ideological threats</i>	Oppression & Threats
<i>Structural Challenges</i>	Oppression & Threats
<i>Modern distractions,</i>	Oppression & Threats
<i>Threats to freedom</i>	Oppression & Threats
<i>Modern threats</i>	Oppression & Threats

3.5. Connecting actants with AAD scores

Having consolidated the actantial data from Greimas’ models and established AAD scores for each text, we then explored how the six actant roles (Subject, Object, Helper, Opponent, Sender, Receiver) might correspond with AAD levels. To test this, we employed an Exploratory Multiple Factor Analysis (MFA), followed by HDBSCAN (hierarchical density-based) clustering.

First, we compiled all relevant variables - six columns for the actant roles and one numeric column representing the antagonism score - into a single dataset. MFA was conducted using the *FactoMineR*⁶ package, with one block of variables corresponding to the six actant roles and a second block for the antagonism score, to uncover common dimensions that capture both the structure of the actant roles and the continuous variance in antagonism. Following the MFA, we extracted the factor coordinates reflecting the combined actantial configuration and the AAD scores. We then applied HDBSCAN to identify clusters of texts whose narrative structures and AAD scores are similar while labeling as outliers any texts that did not belong to a dense region.

Because HDBSCAN can flag a subset of observations as outliers (labeled cluster “0” in the results below), we performed a second pass of HDBSCAN specifically on those outliers. This two-stage procedure allowed us to detect whether outliers formed coherent subclusters. Finally, each text’s first- and second-pass cluster assignments were saved in a tabular form to facilitate further interpretation. Graphical outputs such as scree plots of variance explained and two-dimensional scatterplots of the factor coordinates colored by cluster membership were generated to aid in visualizing how antagonism intensity aligns with or diverges from particular narrative structures. Through this combination of MFA and iterative HDBSCAN clustering, the analysis produced a set of clusters representing distinct narrative structures, each of which corresponded with a specific level of antagonism.

All parts of the methodology described above were implemented within a fully automated workflow, which we make freely available⁷. This design allows for a streamlined, end-to-end

⁶ <https://github.com/husson/FactoMineR>

⁷ <https://github.com/REFMF/Cultural-Memory-from-Antagonism-to-Deliberation-in-Social-Media-AI-Approach->

process—once the initial dataset is uploaded, the scripts sequentially execute each stage. By structuring the methodology as a coherent pipeline, we minimize the need for manual intervention and maximize its reproducibility, as each step is automated and documented.

3.6. Other tested methods

- Besides LLM-supported Greimas’ model, we also tried other methods, described below. In *Section 3.6.1*, we present our experiments with neural representation-based topic modeling aiming to directly extract interpretable narratives from texts. In *Section 3.6.2*, we outline our attempt to automate established Deliberative Quality Indicators (DQI) and discuss their effectiveness in assessing the quality of discussions on cultural memory.

3.6.1. Topic modeling for narrative extraction

In addition to the LLM-based approach, we investigate whether topic modeling can be used to extract narratives from social media posts and news articles. Topic modeling approaches aim to group pieces of text into different topics based on keywords and their semantic content. We used the BERTopic model (Grootendorst 2022), which performs topic modeling based on neural text representation. The BERTopic consists of the following steps:

- 1) Embedding documents – We embed input documents (articles or social media posts) into numerical vectors in such a way that documents with similar words give similar vectors. This is done using the sentence-transformers embedding model (Thakur et al. 2021).
- 2) Dimensionality reduction – As Sentence-transformers returns 384 dimensional vectors, BERTopic reduces them to 5 dimensions using dimensionality reduction techniques such as UMAP (McInnes, Healy, and Melville 2018) (local similarity preservation technique) or PCA (Pearson, 1901) (Global similarity preservation technique). This improves performance for the subsequent tasks;
- 3) Topic clustering – In the reduced space, documents with similar vectors are grouped into topics using HDBSCAN clustering. Since the documents with similar vectors contain similar content, this produces groups (topics) of documents with similar contents;
- 4) Topic representation – Groups of documents representing the same topic are described with keywords and phrases that best describe each topic (i.e. appear most often in its documents).

While topic modeling produces a statistically relevant distribution of keywords in the dataset, a major disadvantage of this approach is that there is no guarantee that the produced topics will reflect our intention, i.e. identifying the structure of cultural memories and that they are going to match the desired narratives or roles present in Greimas’s model. Unlike LLMs, we cannot guide the BERTopic model using prompts. Therefore, we are more likely to get general topics based purely on semantic similarity between texts. Our Resistance Day use case confirms this shortcoming. The results of this analysis are presented in [Appendix D](#)⁸.

⁸ <https://github.com/REFMF/Cultural-Memory-from-Antagonism-to-Deliberation-in-Social-Media-AI-Approach-/blob/main/Appendix%20D%3A%20Bertopic%20results>

3.6.2 Applying DQI indicators to investigate deliberative quality

Initially, we aimed to evaluate different articles and social media discussions by utilizing established deliberative democracy quality indicators, e.g., DQI (Deliberative Quality Indicator) (Steenbergen et al., 2003) and DQI2 (Bächtiger et al., 2009). Our preliminary results, particularly in developing the mutual respect indicator, were promising.

However, we opted to replace the initial additive approach with a summative one (Bächtiger & Parkinson, 2019). Given the complexity of the cultural memories, a multilayered and more structured discursive approach proved necessary. At the same time, context identification and analysis emerged as essential components - tasks that individual deliberative quality indicators cannot assess while LLM-based tools are well-suited to perform.

3.7. Data Sources

The described methodology was developed and applied to a case study examining Slovenian commemorations of the Day of Resistance. We used two types of data: social media posts from X and traditional media articles from online news sources.⁹

For the social media analysis, we collected X posts covering the period from April 2023 to April 2024. This dataset was gathered by Sciences Po under the SoMe4Dem project. The collection focused on commemorative discussions in Slovenian, comprising 753 posts. The dataset includes the full text of tweets, quotes, and retweets, as well as metadata such as language, timestamp, user ID, screen name, and external links. Additionally, variables indicate whether a post is a retweet or a quote. The X dataset was compiled based on the following query terms: "Dan upora proti okupatorju" and "Dan upora". These keywords were selected to capture discussions related to the Day of Resistance and its broader commemorative context in Slovenia. The collection included special-character normalization, ensuring the retrieval of all relevant posts.

To analyze traditional media, we collected relevant news articles using Media Cloud, an open-source platform developed by the Berkman Klein Center for Internet & Society at Harvard University, which compiles and organizes online news content to facilitate research on attention, representation, influence, and language in global media ecosystems (Roberts et al., 2021). The Slovenian database was queried using the following 14 case-sensitive keywords: »dan upora«, »dnevu upora«, »dan OF«, »dneva OF«, »proti okupatorju«, »državna proslava«, »državne proslave«, »državni proslavi«, »dan spomina«, »dnevu spomina«, »osvobodilna fronta«, »osvobodilne fronte«, »protiimperialistična fronta« and »protiimperialistične fronte«. Additional news material was collected through links found in the X dataset and manually retrieved from three Slovenian weekly publications: Delo, Demokracija, and Mladina. We included all relevant news articles published on this topic for three consecutive years, from 2022 to 2024. Overall, 144 irrelevant or duplicated articles were identified, thus reducing our dataset from 308 to 164 articles.

⁹ Data curation: Darko Darovec and Žiga Oman participated in collecting and organising sources on the Day of Resistance commemoration - Darovec focusing chiefly on scholarly studies, Oman on traditional media articles.

4. Evaluation of the methodology

The analytical methodology described in *Section 3* allows for a wide-scale automatic analysis of (social) media texts and provides human interpretable outputs concerning the role of cultural memory in deliberative democracy. However, before we provide and interpret the results in *Section 5*, it is crucial that we validate the scientific apparatus used to confirm that LLM-based methodology produces similar results to manual analysis. Only successful evaluation can give credence to our methodology and ensure trust in the results.

For each of the three LLM-supported methodological steps (described in *Sections 3.1, 3.2, and 3.3*), we compare GPT-4o outputs with those of human experts. In *Section 4.1*, we first perform quantitative and qualitative comparisons of AAD analysis and discourse functions analysis. In *Section 4.2* we evaluate Greimas actantial narrative model, and in *Section 4.3*, we draw conclusions about the similarities between human and LLM-based performance and the overall utility of the automated approach.

For all manual analyses, we asked human experts to manually perform the same three analyses on a sample of both news articles (N=18) and X comments (N=30).

4.1 Evaluation of AAD analysis and discourse functions ratings

First, we evaluated inter-rater reliability for the discourse function and AAD analysis between the experts and the LLM using three different measures – absolute agreement (%), Krippendorff's Alpha, and Intraclass correlation.

The five discourse function parameters were annotated on an interval scale ranging from 0 – 100 that was normalized to a 10 - point scale for the human annotator. The absolute agreement was calculated as a percentage of cases in which the GPT-4o rating matched the human rating within a ± 2 margin. Given the interval-level nature of the data, a ± 2 difference was considered an acceptable boundary to capture near-equivalent ratings, while still distinguishing larger discrepancies. This measure provides an intuitive metric of how often the LLM's scores closely approximate those of human experts.

We also employed both intraclass correlation coefficients (ICCs) and Krippendorff's alpha to assess the consistency of our LLM. We chose the ICC because it is a robust measure that captures not only the correlation but also the consistency between two sets of continuous measurements, making it well-suited for interval data. We assessed the effectiveness of our LLM by directly comparing its scores to a single human expert's ratings, thereby focusing on how consistently the LLM replicates this particular expert's judgments. According to the guidelines presented by Koo & Li (2016), we choose the Two-way mixed-effects model ICC (3,1) with a consistency definition since we want to track the LLM reliability rather than exact numerical agreement. To complement the ICC, we further calculated Krippendorff's Alpha, as it is frequently employed in content analysis and accounts for chance agreement.

*Table 3: Inter-rater reliability statistics for the discourse functions and AAD analysis for news articles and X comments. A stands for news articles, X for Twitter/X Comments, Ka for Krippendorff's Alpha, ICC for Intraclass correlation, AA for Absolute Agreement. The significance of the differences is denoted as follows: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.*

Category	A - K α	A - ICC	A - AA	X - K α	X - ICC	X - AA
Epistemic f.	0,45	0,51**	83,3%	0,13	0,22	80%
Ethical f.	0,60	0,61**	83,3%	-0,11	0,11	60%
Ideological f.	0,63	0,66***	88,8%	0,16	0,14	50%
Democratic f.	0,58	0,57**	77,7%	-0,08	0,08	70%
AAD score	0,69		66,60%	0,41		43,3%

Table 3 presents the reliability statistics for the discourse functions and AAD analysis divided by news articles (A, left-hand part) and X comments (X, right-hand part). For news articles, moderate to substantial reliability was observed, with ICC (3,1) values ranging from 0,51 ($p < 0,01$) to 0,66 ($p < 0,001$), Krippendorff’s alpha ranging from 0,45 to 0,69, and absolute agreement reaching as high as 88,8%. In contrast and expectedly, the reliability for X comments was lower. Although low Alpha and ICC values indicate weaker agreement, absolute agreement for X comments varied between 50% and 80%, suggesting that there were still numerous instances of close scoring within the ± 2 margin. We observe a similar trend in the reliability for AAD scores, where Krippendorff’s Alpha indicates an acceptable level of inter-coder reliability for news articles but a lower level for X comments.

These findings suggest that GPT-4o more reliably replicates human-like judgments in longer, more formal texts and performs somewhat less consistently on semantically sparse X comments. This is not surprising, considering that X posts are short and hard to label even for much easier tasks such as sentiment analysis, where human inter-annotator agreement is between 0.42 and 0.67, and even self-agreement is only between 0.46 and 0.84 (Mozetič et al 2016). Nonetheless, even among X comments, absolute agreement within the ± 2 range remained relatively high for several dimensions. It is also noteworthy that the X dataset was comprised mostly of shorter tweets, making it more challenging to extract extensive qualitative details. Under such constraints, achieving high agreement levels, whether among human annotators or between humans and LLMs, can be difficult.

4.2 Evaluation Graimas actantial roles

In evaluating the inter-annotator reliability for actantial roles, we recognized that individual actants are very abstract and can be named in multiple ways, rendering an exact name-matching approach impractical. Instead, we presented two human expert annotators with the actants and characters generated by GPT-4o alongside each original text and asked them to indicate their level of agreement on a 1–5 scale (1 = completely disagree, 5 = completely agree). This approach allowed us to accommodate for the inherent abstraction of actantial designations while still gauging whether GPT-4o’s output adequately captured the text.

Table 4: Agreement scores (their means and standard deviations) between human expert annotators and LLMs assigning Greimas actantial roles for news articles. The Mean Absolute Difference (MAD) shows the average difference between human annotators.

Actant Role	Human 1	Human 2	MAD
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Subject Actant	4,35 ± 0,63	4,94 ± 0,27	0,57
Subject Character	3,86 ± 0,86	4,29 ± 0,61	1,00
Object Actant	4,86 ± 0,36	4,57 ± 0,51	0,43
Object Character	4,50 ± 0,76	4,07 ± 0,83	0,86
Sender Actant	3,93 ± 0,83	4,79 ± 0,58	1,00
Sender Character	4,29 ± 0,91	3,50 ± 1,02	1,64
Receiver Actant	4,29 ± 0,47	4,93 ± 0,27	0,64
Receiver Character	4,14 ± 0,66	4,64 ± 0,63	0,64
Helper Actant	4,29 ± 0,73	4,50 ± 0,52	0,21
Helper Character	4,14 ± 0,95	4,21 ± 0,80	0,93
Opponent Actant	4,64 ± 0,63	4,64 ± 0,50	0,57
Opponent Character	4,64 ± 0,75	4,07 ± 0,83	1

Table 4 presents the agreement scores (means and standard deviations) for two human expert annotators along with their Mean Absolute Difference (MAD) values for news articles. The MAD serves as an intuitive measure of annotator agreement, with lower values indicating stronger consistency between raters.

Overall, both annotators rated GPT-4o’s outputs favorably, with mean values often exceeding 4, indicating a high level of agreement. The largest discrepancy arose in “Sender Character,” where Annotator 1 reported a mean agreement of 4.29 (± 0.91), while Annotator 2 reported a mean agreement of 3.50 (± 1.02), resulting in a MAD of 1.64. By contrast, the “Helper Actant” category showed the greatest convergence (MAD = 0.21), along with notably higher and consistent scores. These results suggest that, despite some variability in how the annotators perceive the validity of individual actantial roles, GPT-4o’s actant detection capabilities were generally evaluated as valid and coherent.

As seen in Table 5, for the X comments, both annotators provided lower overall scores of agreements with LLM and also showed greater variability in their evaluations, as reflected in the higher mean absolute differences. Annotator 1 scores ranged from 2.70 to 3.23, whereas Annotator 2 scores varied between 3.43 and 4.40, resulting in an overall average mean that still indicates a moderate level of agreement with GPT-4o’s actant assignments. Discrepancies between annotators were especially pronounced in “Receiver Character” (MAD = 1.57) and “Opponent Actant” (MAD = 1.50), highlighting notable divergence between the two experts’ assessments of GPT-4o’s output.

Table 5: Agreement scores (their means and standard deviations) between human expert annotators and LLMs assigning Greimas actantial roles for X posts. The Mean Absolute Difference (MAD) shows the average difference between human annotators.

Actant Role	Human 1	Human 2	MAD
Subject Actant	2,80 ± 0,66	3,97 ± 1,22	1,43
Subject Character	3,00 ± 3,43	3,43 ± 1,36	1,3
Object Actant	3,23 ± 0,77	3,77 ± 1,31	1,2
Object Character	2,93 ± 0,91	3,43 ± 1,31	1,1
Sender Actant	3,17 ± 0,70	4,00 ± 1,29	1,37
Sender Character	2,96 ± 1,00	3,53 ± 1,22	1,23

Receiver Actant	$3,23 \pm 0,57$	$4,40 \pm 0,77$	1,23
Receiver Character	$2,97 \pm 0,56$	$4,33 \pm 0,88$	1,57
Helper Actant	$2,80 \pm 0,96$	$3,93 \pm 1,41$	1,33
Helper Character	$2,70 \pm 1,01$	$3,70 \pm 1,37$	1,13
Opponent Actant	$3,10 \pm 1,19$	$3,93 \pm 1,23$	1,5
Opponent Character	$3,17 \pm 1,21$	$3,70 \pm 1,24$	1,27

4.3 Utility of automated LLM-based analysis

Taken together, the three evaluations, covering discourse functions, antagonism-deliberation nexus, and actantial narrative analyses, demonstrate that GPT-4o can achieve moderate to strong alignment with human annotators, especially for longer and more context-rich texts like news articles. X comments, being shorter and semantically more ambiguous, posed greater challenges for both human annotators and GPT-4o, leading to lower reliability and higher variability. Nonetheless, absolute agreement within the ± 2 point margin remained reasonably high for certain categories, indicating that even in less-than-ideal textual conditions, GPT-4o’s outputs well approximate human judgments. Overall, the evaluations’ findings justify the application of the proposed automated methodology in a wide-scale analysis of standard and social media texts. We present the results of such an application in *Section 5*.

5. Results

In this section, we present the results of applying our methodology (presented in *Section 3* and evaluated in *Section 4*) to the social media posts and text from traditional media (data are described in *Section 3.7*) related to our use case – cultural memory of Slovene Resistance Day (see a short description of its controversial nature in *Section 1* and *Section 2.2*). A wider and deeper discussion of the methodology and results is deferred to *Section 6*.

Overall, we identified 28 actants in the news article dataset and 53 actants in the X dataset. In news articles, 4 actants were assigned to the subject role, 7 to object, 6 to sender, 3 to receiver, 4 to helper and 4 to the opponent role. In contrast, the X posts dataset yielded 53 distinct actants, reflecting a richer diversity of discourse in user generated posts: 10 subject clusters, 8 object clusters, 12 sender clusters, 6 receiver clusters, 8 helper and 9 opponent clusters. The 28 actants identified in the news article dataset produced a total of 12 coherent narrative actantial configurations, whereas the 54 actants identified in the X comments dataset generated 21 such structures. The narrative structures represent distinct patterns in commemorative discourse, each structured around a specific actantial configuration, i.e. Subject – Object – Sender – Receiver – Helper – Opponent with added ideological distributions (left, center, right), and quantified with Antagonism–Agonism–Deliberation (AAD) scores, and discourse function

ratings, e.g. epistemic, ethical, ideological and democratic (See tables for news articles and X posts in [Appendix E1](#)¹⁰ and [Appendix E2](#)¹¹)

Overall, we observe that the news articles dataset is structured with more centralized and ideologically stable narratives, while the X comments dataset is fragmented and exhibits higher levels of antagonism. To illustrate these overarching patterns, we present the two most common actantial configurations in both datasets as examples. These examples provide insight into the narrative structures of commemorative discourse, demonstrating how historical narratives are framed, contested, and sustained across different communicative environments.

The most widespread narrative structure (no 6) in the news articles dataset accounts for almost one-third of all identified narratives, with an AAD score of 2.4 (mild antagonism), see *Table 6*. This narrative structure is shaped by a strong emphasis on historical identity and acknowledgment, where ideological positioning plays a critical role in shaping perspectives on national awareness and historical interpretation. This **narrative structure** also holds the most pronounced ideological function in the news dataset, scoring over 76 points, while its epistemic function remains comparatively low, below 68 points. The prominence of this narrative in our dataset suggests that commemorative discourse in news media remains structured yet polarized, with antagonistic engagement primarily emerging in debates over historical memory and its political implications. Across these roles, a predominantly right-leaning distribution emerges: both the Subject and Object are over 65% right-wing, the Sender is 64% right-wing, and the Receiver and Helper also exceed 60% in right-leaning alignment. By contrast, Historical Distortion (Opponent) is majority left-wing (roughly 66%), suggesting that accusations of misrepresenting the past largely travel from the right to the left. This configuration suggests a highly history-focused narrative where debates around national awareness and historical interpretation are largely driven by a right-oriented framing, potentially amplifying adversarial dynamics - consistent with its status as the most antagonistic and widespread structure in the dataset.

Unlike the news articles, where antagonism is often mitigated by elements of agonism and deliberation, the **X dataset** is overwhelmingly polarized. Unlike in news articles, where ideological contestation often follows a structured debate format, discussions in X exhibit high ideological clustering, with little engagement across ideological lines. The overwhelming presence of oppositional framing reinforces an us-versus-them dynamic, in which historical narratives are weaponized to delegitimize opposing viewpoints rather than to foster debate. High antagonism, with AAD score 1, marks **most common narrative structure (no. 4)**, which accounts for over 20% of all identified narrative structures (see *Table 7*).

Table 6: Example of Greimas actants in news narrative structure no. 6 showing mild antagonisms with AAD score of 2.43. This narrative structure contains 32.1% of instances.

¹⁰ <https://github.com/REFMF/Cultural-Memory-from-Antagonism-to-Deliberation-in-Social-Media-AI-Approach-/blob/main/Appendix%20E1-Tabular%20Overview%20of%20Narrative%20Structures%20in%20News%20Articles.pdf>

¹¹ <https://github.com/REFMF/Cultural-Memory-from-Antagonism-to-Deliberation-in-Social-Media-AI-Approach-/blob/main/Appendix%20E2-Tabular%20Overview%20of%20Narrative%20Structures%20on%20X.pdf>

Subject	<i>Historical identity preservation (L-27,9%; C-4,7%; R-67,4)</i>
Object	<i>Historical acknowledgment (L-28,3%; C-2,2%; R-69,6%)</i>
Sender	<i>Ideological Agenda / Historical Interpretation (L-31,9%; C-4,3%; 63,8%)</i>
Receiver	<i>National Awareness / Slovenian Social Future (L-29,8%; C-6,4%; R-63,8%)</i>
Helper	<i>Cultural/Collective Memory / Historical Documentation (L-29,1%; C-5,8%; R-65,1%)</i>
Opponent	<i>Historical Distortion (L-65,9%; C-0%; R-34,1%)</i>
AAD Scores	<i>Mild Antagonism</i>
Epistemic f.	67,4
Ethical f.	62,5
Ideological f.	76,1
Democratic f.	43,7

The narrative structure in this structure reflects a predominantly left-wing alignment, with key elements such as the Subject (Resistance and Independence) and Object (National Sovereignty and Independence) both displaying strong left-wing dominance (69.9%). The Sender (Historical Themes) and Receiver (National Unity) follow a similar pattern, with left-wing actors comprising approximately 59% and 64%, respectively. The Helper (Collective Memory/Empowerment) also exhibits a strong left-wing orientation at 65.8%. By contrast, the Opponent (Sovereignty Threats) is overwhelmingly right-wing (76.7%). This distribution suggests that the narrative is structured around left-wing themes of resistance, national sovereignty, and unity, with historical memory playing a crucial supportive role. However, the low AAD score, and its prevalence (20.7%) indicate that while this narrative is widespread, it does not necessarily exhibit strong agonistic or deliberative characteristics. Instead, it may function as a defensive framework against right-wing sovereignty-related critiques, reinforcing existing ideological divisions.

Table 7: Example of Greimas actants in X narrative structure no. 4 showing antagonism. This narrative structure contains 20.7% of instances.

Subject	<i>Resistance and Independence (LW-69.9%; C-2.7%; RW-27.4%)</i>
Object	<i>National Sovereignty and Independence (LW-69.9%; C-1.4%; RW-28.8%)</i>
Sender	<i>Historical Themes (LW-58.9%; C-16.4%; RW-24.7%)</i>
Receiver	<i>National Unity (LW-64.4%; C-2.7%; RW-32.9%)</i>
Helper	<i>Collective memory/Collective Empowerment (LW-65.8%; C-4.1%; RW-30.1%)</i>
Opponent	<i>Sovereignty Threats (LW-21.9%; C-1.4%; RW-76.7%)</i>
AAD score	<i>Antagonism</i>
Epistemic f.	14
Ethical f.	25,5
Ideological f.	42,1
Democratic f.	15,1

6. Interpretation and discussion

In this section, we elaborate the results from *Section 5* in relation to our three initial hypotheses (see *Introduction*) concerning the impact of social media on discussions about cultural memory in the context of our use case study (Slovenian Day of Resistance). We first examine the transformation of narratives (*Section 6.1*), followed by an exploration of changes in deliberative practices (*Section 6.2*). Next, we address the erosion of epistemic authority (*Section 6.3*), a crucial factor for stable democracy and public deliberation. Finally, in *Section 6.4*, we summarize key insights and recommendations and propose strategies for strengthening deliberation in traditional and social media.

6.1 Hypothesis 1: Narrative Transformation

Our findings support the hypothesis that social media fosters an environment where cultural memory is more personalized, fragmented, and prone to distortion compared to the institutionally anchored narratives in traditional media.

A key indicator is the sheer number of actantial clusters: the social media dataset produced nearly twice as many as the news dataset. This proliferation suggests numerous narrowly defined frames rather than the more consolidated storylines seen in news articles. Where themes do overlap - such as “Resistance and Independence” - social media often split them into smaller sub-themes, frequently defined by specific Opponent or Helper designations.

The social media narratives are also more loosely structured. Whereas news outlets emphasize institutionally grounded motifs (e.g., national identity, collective memory), social media clusters often center on personal or ideological Senders, shorter story arcs, and a wider variety of Opponents (e.g., “Political Opposition,” “Government Oversight,” “Modern Disruptions”). Further, social media showed markedly lower Epistemic Function scores - frequently under 30 points - signaling a heavier reliance on personal claims or contested accounts, whereas news articles often exceeded 60 or 70 points, indicating more robust institutional referencing.

Another dimension of the data asserts this pattern: the Subject–Object–Opponent triad in news articles generally follows a recognizable collective storyline (for instance, “Resistance Remembrance” or “National Identity Preservation” opposed by “Historical Distortion”) and is often bolstered by more explicit Helper roles labeled “Cultural/Collective Memory/Historical Documentation.” On social media, similar narrative structures do appear, but they tend to be scattered among numerous clusters with less consistent naming and more frequent recourse to vague Opponents, such as “Communication Errors” and “Modern Disruptions.” This fluidity not only signifies more personalized vantage points but also underscores the susceptibility of social media discourse to rapidly shifting, individually shaped narratives that do not necessarily align with official or institutional sources.

Taken as a whole, these **indicators confirm the central claim of Hypothesis 1**. The marked increase in cluster count on social media, the predominance of lower epistemic grounding in X comments, and the multiplicity of actant roles referencing historical revisionism or distortion all point toward a more individualized and volatile construction of cultural memory online. While traditional media still grapples with antagonism - often scoring moderately high - it nonetheless integrates memory within broader and more stable institutional frameworks. Social

media, by contrast, not only permits but arguably encourages an ongoing fragmentation of historical interpretation, whereby personal experiences and narrower group perspectives supplant community-validated narratives. Consequently, the data affirm that the affordances of social media do indeed facilitate a shift toward more personalized, contested, and fluid processes of cultural remembrance, in accordance with our original hypothesis.

6.2 Hypothesis 2: Transformed Deliberative Practices

Our second hypothesis posits that social media exhibits more frequent and intense antagonistic engagements than traditional media while simultaneously creating new deliberative opportunities. The data strongly support this claim, evidenced by distinct differences in AAD scores, discourse functions ratings, and actants configurations across the two corpora. These are the key factors supporting this hypothesis:

A key marker of heightened antagonism on social media is the prevalence of clusters with an AAD score of 1 (see [Appendix E2](#)), indicating direct confrontation. These clusters (e.g. 7, 8 and 9) frequently pit revisionist claims (e.g., "Historical Revisionism") against perceived misinformation (e.g., "Historical Distortions"), generating polarized debates over historical truth. The antagonism is high because users on each side of the political spectrum see the other as a fundamental threat to historical truth – marked by radically opposing views on what the Object of “Historical Understanding” and “Truth and Accountability” mean in the context of Slovenian history.

In contrast, traditional media exhibits a broader spectrum of discourse, from moderate agonism to strong deliberation (see [Appendix E1](#)), with narratives anchored in institutional frameworks. For instance, narrative structures 4 (strong deliberation) and 6 (mild antagonism) in the news corpus both address the Subject of “Historical Identity Preservation” versus the Opponent “Historical Distortion,” but differ in their Objects: “Cultural Heritage Preservation” versus “Historical Acknowledgment”. Whereas Narrative Structure 6 foregrounds “Historical Acknowledgment” - implying an effort to reinterpret or reshape collective memory—Narrative Structure 4 centres on “Cultural Heritage Preservation”, favouring continuity and protection of existing interpretations. This difference in Object roles helps explain the disparity in AAD scores between the two structures. The difference is evident also in the ideological function ratings, with narrative structure 4 scoring 49.8 and narrative structure 6 reaching 76.1.

While traditional media moderate antagonism through editorial oversight, social media fosters a bifurcated discursive environment: one dominated by polarization and ideological clashes, and another, albeit less frequent, where agonistic and deliberative exchanges emerge organically. Notably, deliberative clusters tend to be left-leaning, limiting broader ideological inclusivity. In practice, this means that the debates with the AAD score of 3 (deliberation) often remain confined to left-leaning enclaves, limiting the broader societal impact of these more reflective or dialogical discussions. Linking deliberative narratives with a right-wing skew could potentially foster greater cross-ideological synergy.

These findings affirm Hypothesis 2. Overall, social media discourse exhibits both heightened antagonism and fresh opportunities for open-ended deliberation, altering how cultural memory is debated. Traditional media retains more institutionally grounded frameworks, balancing antagonistic and deliberative modes. By contrast, social media fosters rapid, polarized

exchanges and occasional bursts of constructiveness that news articles seldom mirror. Thus, consistent with H2, the platform affordances of social media reshape agonistic and deliberative dynamics in public discourse, amplifying conflict while enabling novel, if sporadic, forms of collaborative sense-making.

6.3 Hypothesis 3: Cultural Memory and the Public Sphere

Hypothesis 3 proposes that social media, by altering how cultural memory is produced and circulated, diminishes the epistemic authority once maintained by institutional media and traditional historical frameworks. The fundamental question is whether the dynamic, user-driven environment of social media erodes factual anchors and inclusivity norms, thus threatening the stability of the public sphere. Drawing on actantial analyses of both news articles and X comments, we evaluate changes in epistemic, ethical, democratic, and ideological functions to ascertain the broader impact on collective meaning-making.

A consistent finding emerging from our dataset is that X comments exhibit markedly lower Epistemic Function than news articles - often below 40, and in some instances, dipping into the single digits. By contrast, many news clusters score 60–80+. This disparity implies that institutional media retain a more robust factual grounding rooted in recognized archives, historical documentation, and editorial standards.

Frequently in X clusters, the Sender of “Historical Revisionism” and “Historical Themes” – directs its message toward the Receiver of “Public Insight” with the opposition of the Opponent “Historical Distortions,” generating politically charged, highly ideologically motivated and not necessarily fact-driven content (frequent misinformation and disinformation occur) – with specific aim to provide (re)interpretative insights on Slovenia’s past. Short-form commentary typically lacks rigorous source citation or editorial checks, allowing contested facts, revisionist frames, and partial truths to proliferate. Consequently, epistemic authority - the ability of established narratives to prevail - is undermined.

The Ethical and Democratic Functions of X comments similarly tend to be lower than in news articles, with many X clusters registering scores below 40 in Ethical Function and frequently even lower in Democratic Function. This pattern suggests a reduction in moral framing and inclusivity, making it more difficult to foster mutual accountability or construct common ground. Where news texts incorporate “Historical Documentation,” “Collective Solidarity,” or “Supportive Alliances” as Helpers - thus promoting broader societal and factual considerations - X comments often emphasize personal antagonisms or ideological stances without a corresponding emphasis on collective moral responsibility, with Helpers being frequently “Ideological Support” and as a counterpart to articles epistemic grounded emphasis of “Historical Documentation” – a rather vague Helper of “Historical Study” is present, including short often contentious statements either reinforcing the Day of Resistance or undermining it, often with subtle misinformation coupled with rhetorical undertones.

Meanwhile, the Ideological Function in X remains moderately high (40–70), indicating abundant political motivation but weaker shared factual or civic frameworks. Traditional media, though also ideological, benefits from stronger epistemic anchors and editorial oversight, helping maintain clearer references to national or institutional memory and more reliable factual baselines.

Collectively, lowered Epistemic Function and diminished Ethical and Democratic dimensions in social media raise serious concerns for the stability of the public sphere. High volumes of user-driven commentary favor personalized or revisionist stances, fracturing recognized historical narratives. Antagonistic narrative structures - where Subject, Sender, and Opponent center on historical truth, revisionism, or distortions - further undermine consensus on factual premises.

Despite these concerns, some “pockets” of constructive engagement appear—albeit infrequently. Clusters coded with an ADD score of 3 show that at least a subset of users can engage in more robust questioning of historical events. Whether these pockets can stabilize or expand to sustain a more deliberative dialogue is uncertain. The data nonetheless confirm that social-media-driven transformations of cultural memory, on balance, undermine established epistemic authority and compromise the cohesive functioning of the public sphere.

In evaluating H3, the evidence strongly suggests that social media’s restructuring of cultural memory - through lower epistemic grounding, weaker ethical/democratic frameworks, and frequent ideological conflict - does indeed threaten both the stability and coherence of the public sphere. While traditional media, with higher Epistemic and Ethical Functions, preserves certain baseline standards, the rise of short-form commentary competes with these narratives and intensifies the risk of fragmentation. Though some constructive dialogue exists on X, the overall trend is one of polarization. Thus, **H3 is substantially validated**: social-media-driven shifts in cultural memory diminish epistemic authority, challenge democratic stability, and complicate the creation of a shared historical narrative in contemporary public discourse.

6.4. Strengthening deliberation: Key Insights and recommendations

Our analysis highlights specific structural elements that foster deliberation and prevent discussions from devolving into polarization. To enhance deliberative quality in discussions on cultural memory, particularly in news media and social media (X/Twitter), several key strategies emerge:

1. Deliberation improves when **opponents are clearly defined**. In news discourse, debates structured around concrete opponents, such as Societal Division or Foreign Occupation, allow for more constructive engagement. In contrast, on social media, discussions often remain vague, with antagonist actants described in broad and ambiguous terms like "Modern Disruptions" or "Communication Errors," which prevents meaningful engagement. Encouraging users to articulate the core issue at stake more precisely could significantly improve deliberative potential in both domains.
2. A key factor in strengthening deliberation is **maintaining high epistemic and ethical anchors**. As expected, our findings indicate that deliberative spaces emerge when discussions include well-supported historical or ethical framing. News clusters with strong epistemic and ethical functions - often featuring expert analyses, moral imperatives, and references to historical documentation - tend to sustain structured debate. On social media, discussions that explicitly reference historical narratives or ethical imperatives, such as “Quest for Truth” or “Historical Significance,” correlate with higher deliberation scores. In both contexts, promoting expert-driven content, historical documentation, and evidence-based discourse can serve as a countermeasure against low-information antagonism.

3. Although **strong agonism** is often perceived as a barrier to deliberation, our analysis suggests that it can serve as a catalyst for productive discourse when epistemic and ethical grounding is strong. News clusters with high agonism scores and social media discussions with high deliberation scores demonstrate that structured contestation can maintain engagement even in ideologically charged debates. Encouraging such contestation while ensuring that discussions remain constructive rather than purely adversarial can enhance deliberative potential.
4. Another crucial factor influencing deliberative engagement is how discussions **frame their intended receivers**. In newspaper articles, debates centered around “National Awareness” or “Slovenian Social Future” rarely descend into destructive antagonism. This suggests that a shared sense of collective purpose strengthens deliberation by providing participants with a common reference point. On social media, by contrast, receivers tend to be more fragmented, with discussions framed around “Public Insight”, “Sociopolitical Stability,” or “Slovenian Society”. This fragmentation makes it harder to sustain deliberative engagement, as a significant proportion of threads remain locked in antagonism. Discussions that successfully tie debates to broader societal goals - such as preserving sovereignty or democratic resilience - tend to achieve higher deliberative scores and maintain a more constructive exchange.
5. To foster better online deliberation, platforms could introduce **targeted interventions** (e.g., digital nudges). Encouraging users to clarify their opponents would help shift discussions away from reactionary antagonism and toward more substantive debates. Providing references to authoritative sources, such as historical archives or expert commentary, would enhance the epistemic credibility of discussions. Additionally, framing discussions around shared societal goals rather than identity-based polarization could help transform antagonistic exchanges into more deliberative ones.

By examining actantial configurations, our analysis identifies where deliberation is most likely to thrive and how discussions can be structured to support constructive engagement. Clearer narrative goals, stronger epistemic and ethical framing, and well-defined opponents all contribute to sustained deliberation, particularly in news discourse. While deliberation on social media remains more fragile, historically grounded discussions and structured debates around collective memory show promise in fostering higher-quality engagement. These findings provide actionable insights for journalists, policymakers, and digital platform designers seeking to enhance deliberative quality.

6.5 Limitations and Methodological Considerations

While the study provides strong evidence to support our hypotheses, certain limitations of our research must be acknowledged. Although **quantitative metrics** offer valuable insights, they alone do not fully capture the complexity of discursive interactions. To ensure a more comprehensive understanding, we adopted a discourse-focused approach that integrates structural narrative analysis with discourse analysis and semantic analysis with a semiotic perspective (discourse function ratings and AAD scores), with an emphasis on qualitative interpretation. This methodological shift allows for a more nuanced assessment of the socio-political discourse surrounding commemorations. Specifically, AAD scores and discourse function ratings reveal discursive trajectories - that is, tendencies in antagonistic, agonistic, and deliberative interactions - whereas actantial narrative analysis explains how these tendencies are embedded and narrated within broader cultural memory frameworks.

A potential concern in our approach is **structural overfitting** – the risk of imposing an actantial structure onto short texts that may not explicitly manifest deep narrative functions. However, within our framework, this is not a limitation but rather a methodological advantage. First, our approach relies on semiotic inference, which operates contextually, ensuring that actantial roles are interpreted relationally – both within the text itself and in the specific discursive conditions in which it is articulated. Second, because this inference is applied consistently across a large dataset of shorter texts, emergent structural patterns are not merely artifacts of isolated cases but instead offer statistically valid insights into broader discursive trends. Finally, this method enables systematic, structural statistical analysis of large datasets – in our case, data from X on the topic of the Day of Resistance – offering insights into recurring actantial configurations that would be difficult to detect through traditional qualitative approaches or linguistically focused quantitative methods.

Another methodological challenge is **potential confirmation bias** and distortions introduced by algorithmic pattern recognition. Given the hypothesis-driven nature of this research, there is a risk that findings align with expected outcomes, potentially overlooking contradictory evidence. Moreover, the reliance on LLM-based tools (OpenAI, 2023) introduces an additional interpretive layer. To address this, results were systematically cross-validated through qualitative discourse analysis and a human-annotated subset, using Krippendorff's Alpha to assess inter-annotator reliability (see *Section 4*). Additionally, **noise introduced by statistical analysis and clustering** methods such as HDBSCAN and dimensionality reduction (UMAP) can affect results. While computational techniques facilitate large-scale pattern recognition, they may inadvertently produce distortions. To counteract this, our methodology optimized the silhouette score as an objective measure of clustering quality and included manual validation of actantial groupings.

Furthermore, the **justification for different AAD scales** (six-point for news media, three-point for X comments) reflects the distinct linguistic and structural properties of each text type. News articles, with their richer linguistic variations and more stable narrative structures, allow for finer distinctions in antagonism. In contrast, X comments, being shorter and less structured, necessitate a simplified AAD score scale. This methodological decision ensures that deliberative function indicators are aligned with the antagonism framework while accounting for textual complexity.

Finally, **the scale and thematic focus of the dataset** also pose methodological considerations. While large-scale computational techniques were employed, the study does not fully qualify as "big data" since it focuses on a single commemoration (Day of Resistance) within a defined timeframe. This was a deliberate choice to control for thematic variation and ensure coherence in actantial role analysis and to allow for qualitative analysis and expert evaluation. However, it also means that recurring ideological and historical themes may reinforce existing actantial structures. Comparative analysis across commemorations is necessary to determine whether structural tendencies hold across different cultural memory debates. This will be the topic of our further work.

6. Conclusions and Future Research

This study provides a novel, computationally grounded approach to analyzing how social media reshapes cultural memory and deliberative practices. By integrating actantial analysis, antagonism–agonism–deliberation (AAD) scoring, and discourse function evaluation, we

systematically compared social and traditional media discourse. On the use case of the Slovenian Day of Resistance, we demonstrated that our research allows for a fine-grained examination of how historical narratives are constructed, contested, and transformed across different media environments in relation to different discursive modes. The findings of this study also have significant policy implications. The identification of antagonistic, agonistic, and deliberative narrative structures provides a foundation for developing strategies to counteract polarization and enhance constructive debate. Policymakers and platform designers could explore interventions that encourage agonistic engagement over destructive antagonism, ensuring that historical debates remain part of a deliberative democratic process rather than devolving into ideological entrenchment.

Building on presented insights, further research should further explore how antagonistic discourse might be pivoted toward agonistic engagement, i.e. examining the conditions under which ideological opponents engage in productive debate. This requires a novel longitudinal methodological approach, tracking shifts in antagonistic, agonistic, and deliberative dynamics over multiple years and across various commemorative events. Additionally, the study of epistemic diversity in digital discourse remains an important step. While our findings suggest that institutional narratives retain epistemic authority in traditional media, social media enables alternative historical framings that challenge dominant interpretations. Future research should analyze how historical accounts are adapted, contested, or legitimized within digital platforms, assessing whether social media merely reacts to institutional discourse or actively generates new, competing historical narratives.

Another key avenue of investigation lies in the structural and algorithmic influences on historical deliberation. Our research highlights how platform affordances and recommendation algorithms shape engagement patterns, yet a deeper examination of how these affordances influence ideological clustering, deliberative openness, and memory conflicts is necessary. Future studies could incorporate semiotic square analysis (Greimas, 1987) to explore contradictions and ideological oppositions within memory narratives, while modal analysis (*devoir-savoir-pouvoir-faire*) could refine our understanding of agency and constraints in commemorative discourse. Expanding actor-chain and character-chain configurations, alongside the actantial model, would further illuminate the role of individual agency versus structural positioning in shaping public memory or in other discourses.

This study further underscores the importance of digital literacy initiatives, fact-checking mechanisms, algorithmic transparency, and platform governance strategies in mitigating the political weaponization of history. The computational methodologies employed in our research demonstrate the potential for integrating narrative analysis and discourse function evaluation into policymaking frameworks to strengthen democratic discourse, offering practical insights for fostering more deliberative and resilient democratic spaces.

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