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Final Thesis

BEHIND CONSPIRACY THINKING

An In-Depth Analysis of Textual Structure and
Emotional Patterns in the LOCO Dataset

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Abstract

This thesis conducts a detailed analysis of the LOCO dataset, with a particular focus on exploring the complex connections between relationships among conspiracy texts, emotions, and mental disorders. Employing statistical analyses, the study examines the Forma Mentis networks derived from the LOCO dataset, alongside emotion classification based on the Plutchik wheel. The primary aim is to identify potential common patterns that distinguish conspiracies texts from mainstream narratives. This study highlights how important it is to analyse the relationship between emotions, mental health, conspiracy theories and their texts in order to get important understanding of these interrelated fields.

Summary

1 Introduction

In the complex and often perplexing world we habit, it is natural to search for explanations for events that seem out of our control. While some people find their answers in the official explanations provided by experts and authorities, others search for alternative versions, often in the form of conspiracy theories. These theories propose that inexplicable events are not the result of random or natural processes, but rather the machinations of powerful individuals or groups working in secret to achieve their goals.
As defined in the article “The Conspiratorial Mind: A Meta-Analytic Review of Motivational and Personological Correlates” [1], ≪conspiracy theories refer to causal explanations of events that ascribe blame to a group of powerful individuals (the conspirators) who operate in secret to form hidden plans that benefit themselves and harm the common good (e.g., Uscinski, 2019). Thus, the definitional recipe of conspiracy theories involves three primary ingredients: (a) conspirators, (b) hidden plans, and (c) malintent against others or society; this definitional recipe holds whether conspiracy theories turn out to be true or not (see Brotherton, 2015; van Prooijen, 2018). Conspiratorial ideation, therefore, refers to a tendency to endorse conspiracy theories.≫

Following a common view, conspiracy theories are strictly related to mental illness or personality dysfunctions. One article that go deeper and analyse this statement is the one written by Francesca Naldi, Helga Cristina Avellis and Gloria Vecchi named ”Esiste una relazione fra teorie del complotto e tratti disfunzionali di personalità? Uno studio su giovani inglesi” [2] (literally “Is there a relationship between conspiracy theories and dysfunctional personality traits? A study on young British people”) for the State of Mind journal.
The findings of their study revealed a significant association between conspiracy theory belief and elevated levels of specific personality traits. Notably, individuals who present greater trust in conspiracy theories tended to exhibit higher scores on measures of mistrust, paranoia, cognitive distortion, and negative self-perception.
Mistrust is manifested as a reluctance to trust institutions and authority figures, often viewing them as untrustworthy and malevolent actors.
Simultaneously, an underlying sense of paranoia pervaded these individuals’ worldviews, perceiving the world as a threatening environment, where hidden forces manipulate events to their advantage. This tendency to perform a cognitive distortion of the world further fueled conspiracy theory beliefs. Individuals with this trait tended to interpret information in a biased and skewed manner, often selectively emphasising pseudo-evidence to align them with their pre-existing beliefs. This behaviour reinforced their conviction in conspiracy theories, even if there is evidence of contradictions. Furthermore, individuals who embraced conspiracy theories also exhibited a high sense of negative self-perception. These individuals have a lower sense of self-worth, often viewing themselves as marginalised or powerless individuals. This perception of vulnerability may have contributed to their susceptibility to conspiracy theories, offering a sense of empowerment and control in a perceived chaotic world.
The article underlines also that several other studies have been performed on the subject. For instance, Furnham and Grover (2021) revealed a positive correlation between conspiracy theory beliefs and traits such as narcissism, psychopathy, and histrionic personality disorder. These observations suggest that individuals prone to these personality characteristics may be more susceptible to adopting conspiracy theories due to underlying psychological

vulnerabilities.
The implications of this research go beyond mere academic curiosity. Understanding the link between conspiracy theory beliefs and personality dysfunction implies the possibility of developing strategies to mitigate the effects of these beliefs. By identifying individuals at risk, targeted interventions could be implemented to address the underlying psychological factors.
However, it is important to acknowledge the limitations of the current studies. The sample size was relatively small (450 participants) and restricted to young British individuals, limiting the generalizability of the findings to other populations or age groups. Additionally, the reliance on self-report measures exposed the study to potential biases and misinterpretations.

Despite these limitations, the analysis conducted by Naldi, Avellis, and Vecchi represent an important step toward a deep understanding of this type of phenomenon and the reasons behind it.
At the same time, reducing everything to mental or personality problems is a simplistic view. In reality, the appeal of conspiracy theories comes also from a large variety of psychological factors, as analysed in Melinda Wenner Moyer's article "People Drawn to Conspiracy Theories Share a Cluster of Psychological Features" [3].
One of the factors underlined in this article is the need for control. Conspiracy theories often provide a simplified and reassuring explanation for complex events, offering individuals a sense of dominance over their environment. This can be particularly appealing to those who feel powerless or marginalised in their personal or social lives.
Another key driver of conspiracy theory belief is the perception of a threat. Studies have shown that individuals who feel threatened by external factors, such as terrorism, political instability, or economic uncertainty, are more likely to embrace conspiracy theories. These theories offer a scapegoat, a group or individual to blame for the perceived threats, providing a sense of order and meaning in a world perceived as being out of control.
A fundamental aspect of conspiracy theories emphasised in this research [3] is also the distrust of authority figures and institutions. Conspiracy theorists often view mainstream media, government agencies, and scientific institutions with scepticism, believing that they are deliberately concealing the truth. This distrust comes from a variety of factors, including personal experiences with perceived injustices or a general distrust of institutions that are seen as remote and untrustworthy.
The article [3] explains also that the propensity to believe in conspiracy theories can also be influenced by the so-called "backfire effect". This is the idea that ≪refuting misinformation can just make individuals dig their heels in deeper≫ [3], making the conspiracy-minded person even more convinced of what they believe in. ≪But other research suggests that this putative effect is, in fact, rare. A 2016 paper reported that when scientists refuted a conspiracy theory by pointing out its logical inconsistencies, it became less enchanting to people. And in a study published online in 2018 in Political Behavior, researchers recruited more than 10,000 people and presented them with corrections to various claims made by political figures. The authors concluded that "evidence of factual backfire is far more tenuous than prior research suggests." In a review article, the researchers who first described the backfire effect said that it may arise most often when people are being challenged over ideas that define their worldview or sense of self. Finding ways to counter conspiracy theories without challenging a person's identity may therefore be an effective strategy≫ [3].

In the same research [3] it is highlighted how the pervasiveness of conspiracy theories can have significant negative consequences. They can promote intolerance and prejudice, as they often demonise certain groups or individuals. They can also lead to violence, as they can provide a justification for attacking those who are seen as being part of the conspiracy. Additionally, conspiracy theories about public health issues, such as vaccines and climate change, can have a negative impact on public health by discouraging people from taking necessary precautions.

One main mental disorder has assumed a particular relevance in the common narratives and in different researches: paranoia.
As explored in the article "Paranoia and conspiracy thinking" [4], the two concepts are distinct.
Paranoia, a persistent and unfounded suspicion of others' motives, manifests as a pervasive belief system that permeates an individual's worldview. This distorted perception of reality is characterised by hypervigilance of perceived threats, a tendency to misinterpret ambiguous situations as malevolent, and a pervasive mistrust of others' intentions.
Distinct from paranoia, conspiracy thinking fixates on specific events or issues, attributing their occurrence to a hidden, malevolent force orchestrating events from behind the scenes. Individuals embracing conspiracy theories often perceive themselves as possessing unique knowledge, capable of deciphering the truth hidden from the masses.
Despite their distinct manifestations, paranoia and conspiracy thinking share an underlying psychological basis. Studies suggest that individuals prone to paranoia are more likely to endorse conspiracy theories, indicating a potential link between these two constructs.
A constellation of psychological and social factors contributes to the emergence of paranoia and conspiracy thinking. Personality traits, such as suspicion, distrust, and negative thinking, play a significant role. Life experiences, including trauma, victimisation, and social alienation, also heighten the likelihood of developing these beliefs.
These two issues share also some important consequences that can cause relevant problems not only at an individual level but also to all the collectivity:

- Social Isolation: Individuals embracing these beliefs may withdraw from social interactions due to mistrust of others, leading to isolation and loneliness.
- Violence and Extremism: Paranoia and conspiracy thinking can fuel extremist ideologies and motivate individuals to commit acts of violence against perceived threats.
- Erosion of Trust: These beliefs can erode public trust in institutions, including government, the media, and science, undermining democratic processes and hindering societal progress.

One last article that can help us to have a clear picture of the topic is the one cited above: "The Conspiratorial Mind: A Meta-Analytic Review of Motivational and Personological Correlates" [1].
In this article further details have been added to the study of this subject and in particular it was one of the first meta-analyses to challenge the traditional view of conspiracy as a symptom of mental illness.
The article will be detailed analysed in Chapter 2, but it is important to highlight its main conclusions.
Their findings suggest that conspiratorial ideations are associated with a range of

motivational factors, including:

- Perceiving danger and threat: Individuals who are more likely to believe in conspiracies tend to have a higher sense of threat and vulnerability. They may perceive the world as a dangerous and unpredictable place, and they may be more likely to attribute negative events to adverse forces rather than natural causes.
- Relying on intuition: Daniel Kahneman, a Nobel Prize-winning psychologist, introduced the concept of "fast and slow thinking" in his book "Thinking, Fast and Slow" [5]. According to Kahneman, human thinking can be divided into two systems: System 1 (fast and intuitive) and System 2 (slow and analytical). System 1 operates automatically, relying on quick judgments and heuristics, making it efficient but prone to biases. System 2, based on analytical analysis, is more accurate but consumes more mental resources and is slower compared to System 1.
  The results presented in "The Conspiratorial Mind" article underline how the people who place a high value on intuition and personal experience (essentially the individuals who mainly rely on what Kahneman defined as System 1) tend to be more inclined to accept conspiracy theories. To reinforce their beliefs they tend also to identify patterns and agency in their absence and maintain their views while being close-minded to alternatives.
- Being antagonistic and acting superior: Some research suggests that individuals who are more likely to believe in conspiracies tend to have a more antagonistic and competitive outlook on the world. They may see themselves as part of an elite group who understands the truth about the world, while others are naive or deceived.

Furthermore, from their analysis [1] seems clear that conspiratorial ideations are correlated with various personal traits, in particular:

- Dogmatism: Dogmatic individuals are rigid in their beliefs and resistant to change. They may be less likely to consider alternative viewpoints and more likely to cling to conspiracy theories even in the face of contradictory evidence.
- Low cognitive ability: Some studies have shown that lower cognitive ability is associated with a greater likelihood of believing in conspiracies. In particular, citing directly the article, ≪individuals prone to conspiratorial ideation may also lack the cognitive abilities to evaluate information accurately and critically (see Douglas et al., 2017, 2019). To address this possibility, scholars have directed attention toward the relation between intelligence and conspiratorial ideation. Across studies and measures of intelligence, there appears to be a consistent negative relation between conspiratorial ideation and general cognitive ability, although the magnitude of these relations ranges from small to large≫ [1].
- Need for closure: Individuals with a high need for closure are uncomfortable with uncertainty and ambiguity. They may be more likely to embrace conspiracy theories as a way of making sense of the world and reducing their anxiety about uncertain events.

To make the situation even more complex there is also the fact that the interconnected world where we live in makes it faster for the conspiracy theories to spread. For instance, as reported by "The Associated Press" agency [6] ≪Days after Maui's wildfires killed scores of people and destroyed thousands of homes last August, a shocking claim spread with alarming

speed on YouTube and TikTok: The blaze on the Hawaiian island was set deliberately, using futuristic energy weapons developed by the U.S. military.
Claims of "evidence" soon emerged: video footage on TikTok showing a beam of blinding white light, too straight to be lightning, zapping a residential neighbourhood and sending flames and smoke into the sky. The video was shared many millions of times, amplified by neo-Nazis, anti-government radicals and supporters of the QAnon conspiracy theory, and presented as proof that America's leaders had turned on the country's citizens».
No matter that this reconstruction turned out to be completely false and that the evidence presented referred to events that took place years earlier and had nothing to do with the tragic event in question, a lot of people had already made up their minds about what had happened.

For sure the classic approaches, based on the deep analysis of a phenomenon and on the collection of proof to test if a text content can be classified as conspiracy or not, are the more precise. The downside is that they require a significant amount of time and, as the article [6] showed us, this can mean that in the meantime the conspiracy information can be widely spread.
For this reason, being able to prompt recognise if a text is conspiracy or not is essential and that is the motivation behind this research which undertakes a comprehensive analysis of conspiracy texts with the overall aim of uncovering common patterns and discerning statistically significant differences from traditional discourses.
Studying the emotional basis of conspiracy theories, this research attempts to provide valuable insights into the psychological mechanisms that drive belief systems, potentially identifying strategies to deal with the proliferation of misleading information.
The language of conspiracy (LOCO) corpus, known for its large and varied collection of conspiracy-related texts, is the base of this research. Leveraging the power of the EmoAtlas library, which allows the user to create Forma Mentis Networks and uses Plutchik's wheel to classify emotions into eight distinct types, this study aims to shed light on the emotional dimensions that underlie conspiracy theories. Understanding the emotional background of these narratives is essential, as emotions play a key role in shaping individuals' perceptions and reactions to information.
Furthermore, the comparative approach adopted in this study between the Forma Mentis Network and the emotional patterns obtained from conspiracy texts and the ones obtained from the mainstream aims to identify distinctive features that make these narratives spread. Statistical tests will be used to analyse the data, to make the results objective.

In the following chapters, the approach used, the current knowledge of the subject and a deep analysis of the results obtained in this research will be presented. Moreover, the implications of the results of this study will be discussed, comparing them with what the literature says on this topic.

2 State-of-the-art

As explained in the Introduction, this research aims to uncover common patterns both in the way conspiracy texts are written and in the emotions they contain. To do it, it will be used the novel Python library EmoAtlas which will allow an approach based on the Forma Mentis Networks.
The importance of conducting this type of analysis and research on conspiracy texts lies not only in unravelling the intricate aspects of these narratives but also in understanding their social implications. These texts can influence public opinion, fuel misinformation and contribute to the polarisation of communities, that is why it is essential to act promptly to limit their spread.
For the above reasons, there is a growing interest among researchers in this topic.
Between the existing research, two main studies try to clarify which tend to be the differences between the conspiracy and the mainstream side, even if with two different approaches and focuses:

- The one published on ScienceAdvances called ”Interconnectedness and (in)coherence as a signature of conspiracy worldviews” [7] which, starting from the Loco corpus, focused on the text structure analysis;
- The Psychological Bulletin article named ”The Conspiratorial Mind: A Meta-Analytic Review of Motivational and Personological Correlates” [1] which synthesize 170 studies through a multilevel meta-analytic review that focused mainly on the root causes behind the fact that some individual are more inclined to believe into conspiracy theories than others.

Both of these studies will be deeply analysed in the following Sections.

2.1 Analysis of the ScienceAdvances article ”Interconnectedness and (in)coherence as a signature of conspiracy worldviews”

The Science Advances article ”Interconnection and (in)coherence as a signature of conspiracy worldviews” [7] investigates the linguistic features of conspiracy theories and non-conspiracy texts. The idea behind this article is to test in the LOCO corpus if there are common elements of subterfuge across unrelated or contradictory explanations in the conspiracy theories which can be laid to networks of self-reinforcement belief.

From their analysis, the researchers found that conspiracy theories exhibit a unique pattern of interconnection and coherence.

They start testing the interconnection of the conspiracy documents.
To do it they divide this investigation into two parts: the seed interconnection and the topic interconnection.
Starting from the topic interconnection analysis, the researchers measured the thematic richness by counting the number of ”seeds” present in each document and found that, on average, conspiracy documents contained more seeds than the mainstream ones. Obviously, the analysts used statistical models to show this difference and make the results objective. In particular they ≪fitted a linear mixed-effects regression model predicting the number of seeds contained in documents by subcorpus (either conspiracy or nonconspiracy), adding word count as covariate and nesting documents within websites≫ (as reported in the ScienceAdvances articles[7]).

Furthermore, the study examined the degree of interconnection in networks related to conspiracy and non-conspiracy content. To do it they ≪fitted a linear mixed-effects regression model predicting interconnection (i.e., number of edges per node) by subcorpus (either conspiracy or nonconspiracy) while nesting nodes within nodes' names≫. The analysis revealed that the conspiracy network demonstrated greater interconnection compared to the mainstream network and a visual representation of the results can be seen in Figure 1.
Other analysis has been performed and their output suggested that conspiracy narratives formed larger interconnected components with fewer distinct subnetworks, exhibited higher entropy, indicating a more random arrangement of seeds, and showed greater similarity between connections of conspiracy nodes compared to nonconspiracy nodes. Moreover, various network metrics, such as the clustering coefficient, average shortest path length, and density, indicated higher levels of interconnection within the conspiracy network compared to the non-conspiracy network.

The second step was the analysis of the Topic interconnectedness.
To do it they compared networks derived from LDA algorithm with three different topics numerosity (LDA100, LDA200, and LDA300) for both conspiracy and nonconspiracy themes. In all three sets, the networks related to conspiracy themes showed higher interconnectedness, greater entropy, similar connection patterns among conspiracy nodes, higher clustering coefficients, reduced distance, and increased density compared to non-conspiracy networks.

Another field of interest was the local cohesion.
They assessed the specificity of topics within documents using the Gini coefficient, which measures the inequality in topic distributions. The findings indicated that conspiracy documents exhibited lower topic specificity compared to non-conspiracy documents.

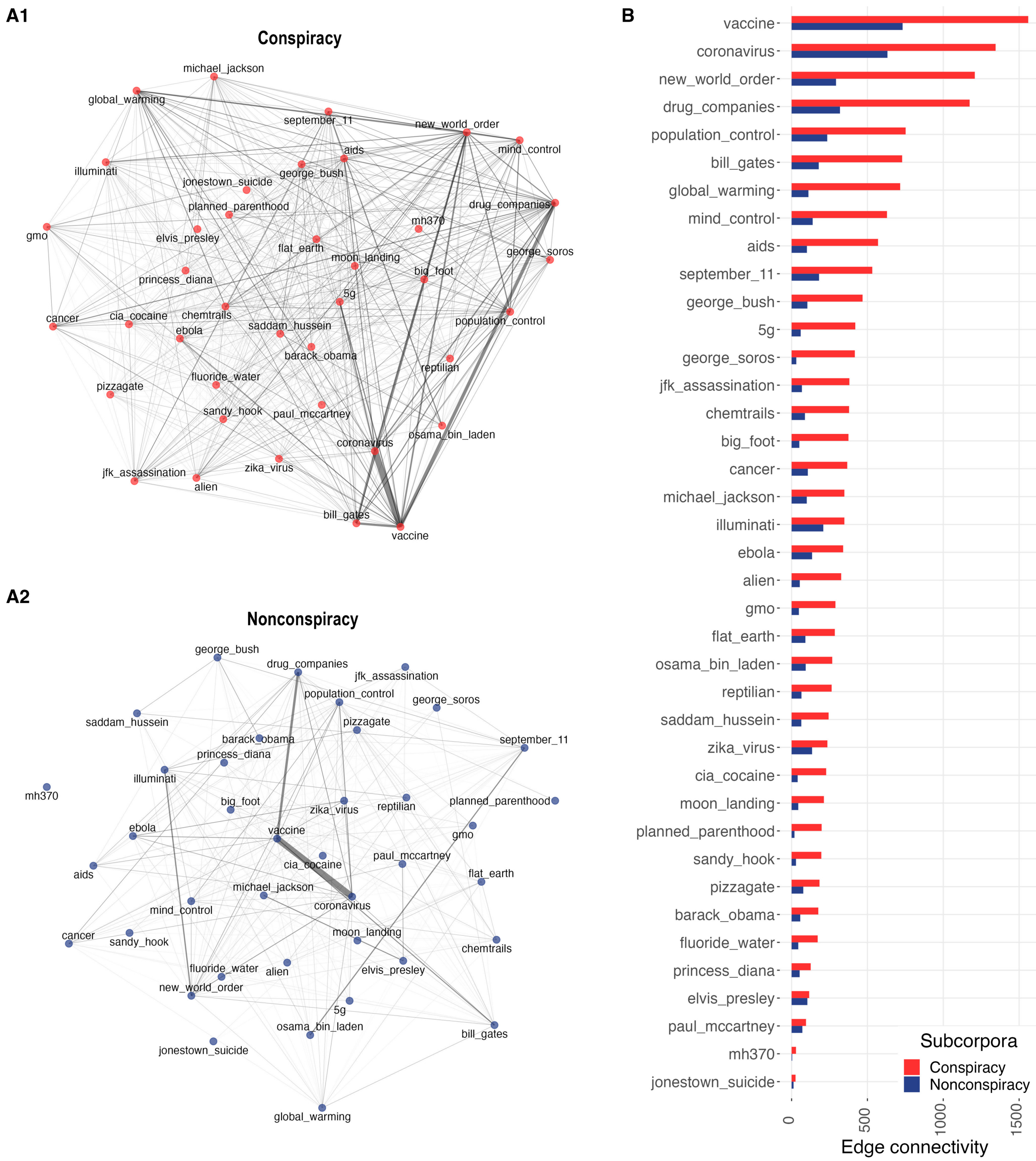

Figure 1: Network interconnection of seeds.
Nodes represent seeds (documents' keywords associated with events that have generated CTs), and edges represent the co-occurrence of seeds in documents. Thicker edges indicate higher co-occurrence. Left: Network plots extracted from the conspiracy (A1) (red) and nonconspiracy (A2) (blue) subcorpora. Right: Numbers of links held by each node (edge connectivity) as a measure of seed interconnection (B). Reproduced by Miani et al. 2022

The study evaluated also the within-document lexical cohesion, which refers to the semantic connectedness between paragraphs. It was discovered that conspiracy documents had lower lexical cohesion than non-conspiracy documents.

Lastly, the researchers analysed global cohesion.
To test the hypothesis that conspiracy documents would exhibit higher similarity among themselves compared to non-conspiracy documents, the researchers used a method called cosine similarity. This method computed the degree of lexical overlap between documents within specific groups (conspiracy or non-conspiracy).
The study excluded documents with the same origin and those obtained from identical websites to prevent similarities arising from shared topics or authors.
They found that, at a global level, conspiracy documents show greater similarity to each other than non-conspiracy documents.

Summing up the results we can say that the researchers found that, as reported in the ScienceAdvances article[7], ≪relative to non-conspiracy texts, conspiracy texts are more interconnected, more topically heterogeneous, and more similar to one another, revealing lower cohesion within texts but higher cohesion between texts and providing strong empirical support for an overarching conspiracy worldview≫.

2.2 Analysis of the Psychological Bulletin article ”The Conspiratorial Mind: A Meta-Analytic Review of Motivational and Personological Correlates”

The article named ”The Conspiratorial Mind: A Meta-Analytic Review of Motivational and Personological Correlates” [1] was published in the Psychological Bulletin 149 in 2023 and it was an absolute game changer on the way the motivations for believing in conspiracy theories was seen.
The great merit of this milestone is that it was one of the first meta-analyses to challenge the traditional view of conspiratorial as a symptom of mental illness. ≪Historically, there has been a focus on the intersection between conspiratorial ideation and abnormal psychological processes.
Scholars have largely focused on two separable, albeit highly related, domains of abnormality and their relations to conspiratorial ideation: (a) personality disorders (i.e., enduring, inflexible, and stable patterns of thought and behaviour that deviate significantly from cultural and normative expectations, leading to marked impairment and distress; see Sleep et al., 2019) and (b) psychopathology (i.e., a broad domain comprising a heterogeneous array of emotional, behavioural, and cognitive dysfunctions that collectively give rise to marked impairment and distress; see Kotov et al., 2021).≫ [1]
The authors argue that while some people who believe in conspiracy theories may have underlying psychological issues, many others are psychologically normal, so they suggest that the complexity behind the choice to believe or not in a conspiracy theory is higher than what has been considered till that moment.

For sure personality is one trait but there is the need to also have what they call motivation. ≪According to one popular perspective (Douglas et al., 2017), people are drawn to conspiracy theories when they experience a deprivation of the following three motivational needs:

- To form a reliable, certain, and stable view of the world (epistemic motives);
- To feel safe and in control, particularly in the face of threat (existential motives);
- To reinforce a superior, albeit fragile, image of oneself and one’s ingroup (social motives)≫ [1].

The article result related to each one of these motives will be in-depth analysed in the following subsections.

The authors claim that by bringing together motivation and personality, it will be possible to clarify what causes conspiratorial ideation and gain a deeper understanding of how and why conspiratorial ideation predicts a host of relevant outcomes. With this approach, we might be one step closer to designing effective interventions for reducing conspiratorial ideation, as both the ”what” and the ”how” will be considered by targeting broad areas of liability.

The main article results are summarised in Figure 2.
Here are grouped into three main categories:

- Threat and Danger;
- Intuition and odd belief/experiences;
- Antagonism and superiority.

These are only the strongest correlated reasons behind a conspiracy thinking and allow us to understand how complex the picture of this field is and how it is simplistic to reduce everything to mental illness.

In particular, in the text, a strong emphasis has been placed on paranoia. It has been stressed that, as some researchers support, paranoia is part of the conspiracist worldview. Several studies, examining the relations between conspiratorial ideation and personality disorder traits, have focused on paranoia, a defining characteristic of paranoid personality disorder. What they obtain supports its centrality to conspiratorial ideation, such that those who score higher on measures of paranoia also report more conspiratorial ideation. Indeed, a recent meta-analysis on the relations between conspiratorial ideation and paranoia indicated that conspiratorial ideation was strongly positively related to it.
In addition to paranoia, scholars have examined the relations between conspiratorial ideation and schizotypal personality disorder, as it is closely related to paranoia. In line with this thinking, conspiratorial ideation manifests medium-to-large positive correlations with total scores on schizotypy measures as well as scores on lower-order schizotypal symptoms, such as unusual and bizarre thinking styles.
Furthermore, it has been specified that ≪Psychopathological symptoms are often organized along two higher-order dimensions: internalizing (e.g., distress, fear, anxiety, depression, low mood) and externalizing (e.g., antagonism, substance abuse, antisociality, impulsivity, irresponsibility; see Kotov et al., 2021) psychopathology. Consistent with the relations between conspiratorial ideation and general personality disorder dimensions (i.e., alternative model of personality disorder traits), conspiratorial ideation is related to a range of internalizing and externalizing features. Regarding internalizing features, conspiratorial ideation tends to manifest small positive associations with total scores on depression symptom inventories (e.g., Bogart et al., 2010; Grebe & Nattrass, 2012; Leone et al., 2018; Rose, 2017) and allied negative mood states, including anger and hostility (e.g., Jolley & Paterson, 2020; Marchlewska et al., 2019). Although no research has examined symptoms of externalizing disorders per se, some research has examined externalizing features in relation to conspiratorial ideation; these studies indicate that conspiratorial ideation is weakly-to-moderately and positively linked with self-reported physical aggression and a willingness to use violence against others (e.g., Lamberty & Leiser, 2019) in addition to justifications of the use of violence (e.g., burning 5th generation mobile network towers to prevent spread of COVID-19; see Jolley & Paterson, 2020). Taken together, conspiratorial ideation appears to be related to multiple manifestations of psychopathology. Even still, abnormal range correlates do not sufficiently account for the fact that conspiratorial ideation is pervasive and perhaps even universal (e.g., van Prooijen & Douglas, 2018). Thus, it is also important to consider normal-range personality in the context of conspiratorial ideation≫ [1].

Lastly, it has been highlighted that they do not find any statistically significant relation with the so-called Big Five traits (extraversion, agreeableness, conscientiousness, neuroticism, openness to experience). This is the model of general personality at the basis of the Cambridge Analytica scandal and that has been often associated with the spread of conspiracy theories.

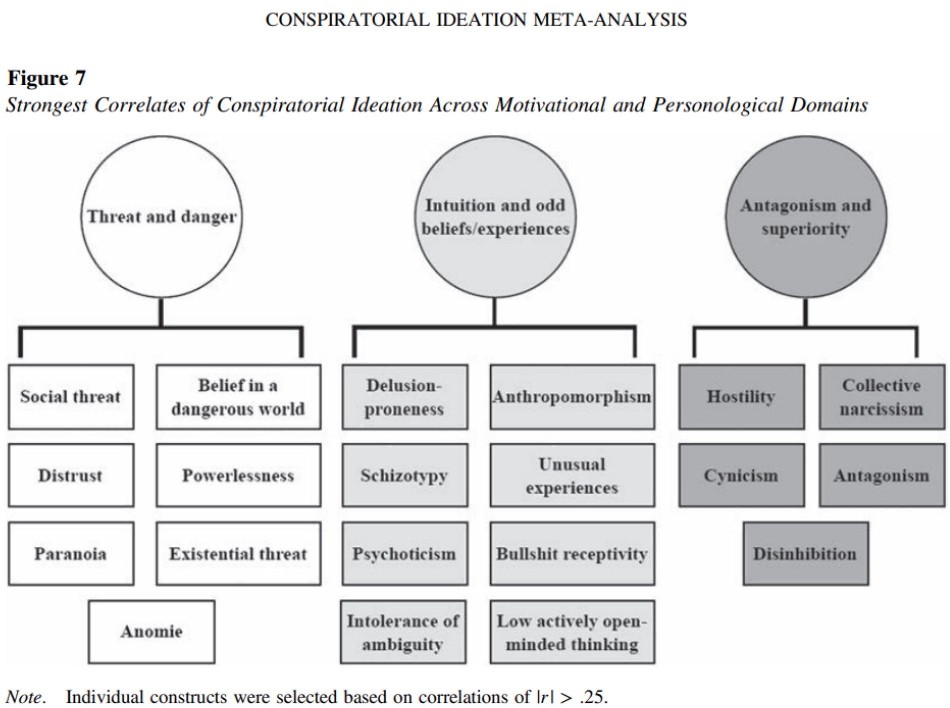

Figure 2: ”The conspiratorial mind”: extraction of the summary of the main causes of the tendency to believe in conspiracy theories. Reproduced by Bowes et al. 2023.

The Psychological Bulletin article and the three main motives behind the propensity to believe into conspiracy: Epistemic motives

By relying on intuition, people can obtain easily understandable explanations for uncertain situations and quickly comprehend the world. These intuitive understandings of the world allow people to find clarity and meaning in their environment. On the other hand, an over-reliance on intuition rather than analytical analysis may lead to a false belief in unverified information, with all its possible negative consequences.
From the article results [1], can be noticed how conspiracy ideas are positively related to the reliance on intuition and the reduction of analytical thinking.
Indeed, conspiracy theories manifest medium-to-large positive associations with measures of intuitive thinking, while they are weakly to moderately negatively associated with self-report measures of rationality and cognitive reflection. These results raise the possibility that individuals prone to conspiratorial ideation tend to try to understand the world by relying on intuition and effortless thinking, rather than complex and analytical explanations.

An overreliance on intuition associated with an approach orientated on find covered explanations can contribute to identifying patterns or agency where none exists. Testing this possibility, the researchers find that illusory pattern perception tends to manifest large, positive correlations with conspiratorial ideation.
Furthermore, individuals prone to conspiracy theories may also lack the cognitive abilities to evaluate information accurately and critically. The researchers have paid attention toward the relation between intelligence and conspiratorial ideation. Across studies and measures of intelligence, there appears to be a consistent negative relation between conspiracist and general cognitive ability, although the magnitude of these relations ranges from small to large.
It seems also that conspiracy theories may be related to a reduced tendencies and motivations in their believers to pursue complexity and a reduced ability to make sense of complex information. This consideration implies that conspiracy ideas are so successful among this group of people because they propose simple explanations to complex problems, making the world they live in understandable.

The Psychological Bulletin article and the three main motives behind the propensity to believe into conspiracy: Existential motives

The next reason presented is the need for control and to feeling safe.
Conspiracy theories may appeal to those with a high level of existential threat, as these individuals are deprived of a sense of security and power.
In addition to perceiving a higher level of threat, the researchers find that conspiracy ideas are moderate to strongly related with the belief that the world is dangerous and unstable, approaching it with cynicism rather than optimism.
Conspiracy ideas are also correlated with a high level of anxiety. In line with this finding, conspiracist show small to medium negative correlations with the perception of control, as an increase in the powerlessness perception means also a higher likelihood of starting to believe in the conspiracy ideas.
Finally, research indicates that conspiratorial ideation is negative related to the feeling of being able to make changes in one's environment.

The Psychological Bulletin article and the three main motives behind the propensity to believe into conspiracy: Social motives

What the researchers found related to the social motives, is that conspiratorial ideation is moderately and positively related to perceiving a large-scale moral breakdown in society and feeling alienated from others.
Conspiracy ideas are also weakly negatively correlated to a healthy and balanced self-esteem and they are weakly to moderately positively related to narcissism. This combinations of results highlight ≪the possibility that people who endorse conspiracy theories are motivated to stand out among their peers and feel entitled to special recognition. That is, those who endorse conspiracy theories may feel they possess secret knowledge about "the truth" that others fail to see or are not knowledgeable enough to possess (e.g., Lantian et al., 2017)≫ [1].

This general mistrust of others may be an important aspect of conspiratorial ideation that turns people away from official narratives and facilitates identifying a clear enemy. The data they analysed converge on an image of conspiratorial ideation being linked to the need to valorize themself, as conspiracists may believe to have special talents and knowledge and at the same time feel sceptical of others.

A similar pattern of relations emerges when examining the relations between conspiratorial ideation and perceptions of one's group. Conspiracists are positively related both to collective self-esteem and to collective narcissism.
In addition the researchers found that conspiratorial ideation is related to perceiving one's group as inherently better than the outgroup, whereas it is negatively related to healthy pride in one's ingroup. Looking at the first point, conspiratorial ideation is strongly related to enhanced threat perception of outgroup members.

3 Emotional patterns in conspiracy content

3.1 The aims of this research

This study aims to provide an additional perspective and insight into the conspiracy world, looking for possible common patterns among the texts they published and employing an innovative approach based on the Textual Forma Mentis Network and the EmoAtlas library. The overarching goal is to uncover any discernible disparities between these conspiracy narratives and their mainstream counterparts both in terms of text structure and emotional shades.

In the text structure analysis, the focus is on discerning differences in the organization of conspiracy texts compared to the mainstream ones. The metrics of diameter, average shortest path length, clustering coefficient and degree assortativity coefficient are computed for each document and topic's Forma Mentis Network. The aim is to discover underlying patterns that could shed light on the distinctive cognitive and reasoning processes employed by conspiracists compared to mainstream thinkers.

On the emotional front, the research pursued to examine the feelings contained in the texts, taking Plutchik's emotion wheel as a starting point. Using the EmoAtlas library, Z-scores for the eight primary emotions are calculated and subsequently compared between conspiracy and mainstream texts. This emotional analysis wants to reveal any notable differences in the emotional landscape of the two types of texts.

In essence, the research attempts to contribute to the understanding of the characteristics of conspiratorial texts, both in terms of text composition and on an emotional level, when compared to traditional texts. Texts can be a benchmark for better understanding both the writer's state of mind but also the way of thinking. The application of a textual Forma Mentis Network approach aims to provide an in-depth understanding of the dynamics behind conspiratorial thinking and its potential divergence from traditional discourse.

3.2 Methods: How the research will be implemented

To fulfil the purpose of this research, different analyses have been performed and a particular focus has been put on the Forma Mentis Networks (Stella 2020) obtained from the documents inside our dataset, analysing both their structures with specific metrics and the emotions that characterise them. Lastly, to make the results stronger and understand their goodness, a comparison will be performed with what other researchers have just discovered in other studies.

To standardise the process and make it more comprehensible, all the analyses performed will follow the same procedure:

1. Will be computed the specific metric analysed for each document taken into account.
2. A grouping of the documents will be made based on the topic assigned by the LDA algorithm.
3. For each topic will be performed a distribution analysis using the Mann-Whitney U Test and the Hodges–Lehmann estimator. The goal of this analysis is to investigate if for each topic there is a difference between the distribution of the Conspiracy and the Mainstream side and (if there is one) establish which tends to have higher value compared to the other.
4. Lastly we can conclude by computing both the ratio at a topic level of the prevalent results obtained in the different topics and the weighted frequencies.

The dataset analysed is the language of conspiracy (LOCO) corpus [8], which is the largest corpus related to the conspiracy world (see Chapter 3.6 for a deep analysis).

Even if it has relevant strengths which probably make it one of the best (if not the best) data collection related to this subject, the LOCO dataset has some problems.

Indeed, there is not a balance between the number of conspiracy documents and the mainstream one. Furthermore, there is also an unbalanced situation if we talk about the number of texts belonging to the two groups on several topics.

In addition, the Conspiracy texts tend to be longer and this characteristic can cause problems in the "traditional" analysis. The use of Forma Mentis Networks removes this issue because it captures the associative and emotional structure of concepts, not focusing on the mere count of words but on their relations.

How these challenges will be handled will be deeply discussed in Chapter 3.7.

It is noteworthy that the starting point for the following research is the work done by the authors of the ScienceAdvances article "Interconnectedness and (in)coherence as a signature of conspiracy worldviews" [7]. In this article, an analysis has also been performed on the LOCO dataset and this allows us to have a reference to deeply understand the dataset and how it is possible to handle its challenges.

3.3 The EmoAtlas library: a description of this novel Python library

EmoAtlas is a novel computational framework that integrates a comprehensive collection of psychological lexicons, natural language processing (NLP) techniques, and network science to automatically extract and analyse emotions and syntactic/semantic word associations in texts [9].

This library introduced a new approach to examining texts and extracting information from them.
To analyse texts and perform emotion profiling, traditionally there are three main approaches:

- The text-based features which want to transform the emotional evaluation into a numerical vector and reduce everything to a sort of regression problem
- The transformers and emotional profiling of texts are a neural network approach made by an encoder which converts the input into a sequence of vectors, while a decoder (after training) can translate the vectors into elements of texts
- The Lexicon-only methods on the other hand use a set of predefined words to identify the emotions

All of these methods have positive and negative aspects.
The text-based features are simple to implement and fast to train but it is sensitive to the data sparsity and starts from the wrong concept that a phrase's meaning is not only the concatenation of the meaning of its words.
On the contrary the transformers approach tends to be more complex (even if nowadays pre-trained versions of massive data are available) and less intuitive/explicable but it has been proved that this method significantly outperforms the other.
Lastly the Lexicon-only method is a good alternative when the computational resources are limited and there is a need for model interpretability but the downsides are that it does not take into account the context of the word and that it will be as good as the relative lexicon.
The EmoAtlas approach offers an alternative to all of them.
Indeed, as defined by its creators Alfonso Semeraro, Salvatore Vilella, Saif M. Mohammad, Giancarlo Ruffo and Massimo Stella in the article "EmoAtlas: An emotional profiling tool merging psychological lexicons, artificial intelligence and network science" [9], ≪EmoAtlas combines lexicon-only and AI-based methods in a uniquely computationally-efficient, interpretable synergy. EmoAtlas uses AI to identify syntactic relationships between words in texts and can perform either text-level or word-level emotional analysis. In the first case, a bag-of-words approach is adopted, relying on EmoLex to capture emotions in texts. In the second case, EmoAtlas uses the network structure to reconstruct the emotional framing of a word by considering its syntactic and semantic associates in text, i.e., those words that were related in text to the target word and thus compose its semantic frame. According to content mapping in the social sciences and frame semantics in psychology, it is possible to reconstruct the connotation of a word by checking other "words that keep company to it" in text: The semantic frame of a concept is the set of words associated either syntactically or semantically to that concept within a given (set) of texts. In network-building mode, EmoAtlas can reconstruct the semantic frame of a target word as a network neighbourhood of syntactic/semantic associates. EmoAtlas can attribute an emotional profile, i.e., a collection of emotional scores, to a target word by analysing its semantic frame, i.e., the set of words

syntactically specifying or semantically related with the target word as synonyms (e.g., ”nature” can also mean ”character”) or hypernyms/hyponyms (e.g., a ”dog” is a type of ”animal”). This is performed through the construction of textual forma mentis networks, which identify syntactic/semantic relationships between words in text.»

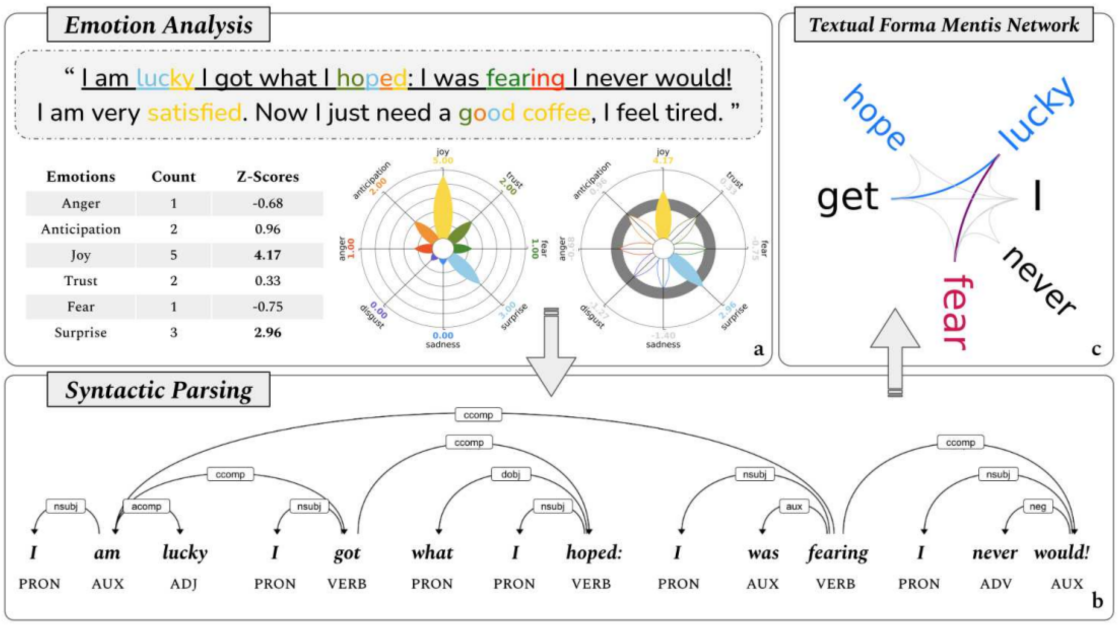

Figure 3: How EmoAtlas works. Starting from the top-left corner a text went through the analysis and EmoAtlas read sentence by sentence and map the emotions. The possible emotions are 8, like the Plutchik’s wheel, and the library can perform both a bag-of-words analysis and a Z-score one. Then each sentence goes through syntactic parsing. The output syntactic tree is used to compute the distance between the non-stopwords. Starting from the distance result, a Forma Mentis Network is created and it can be plotted like in the image in the top-right corner, where the blue links stand for the positive link while the negative are coloured red and the neutral grey. Reproduced by Semeraro et al. 2023.

Figure 3 illustrates an example of the logical process followed by this library and explained above. Summarising it:

- a text went through the analysis and EmoAtlas read sentence by sentence and mapped the emotions
- The possible emotions are 8, like the Plutchik’s wheel, and the library can perform both a bag-of-words analysis that a Z-score one
- Then each sentence goes through syntactic parsing. The output syntactic tree is used to compute the distance between the non-stopwords
- Starting from the distance result a Forma Mentis Network is created and it can be plotted like in the image in the top-right corner, where the blue links stand for the positive link while the negative are coloured red and the neutral grey.

3.3.1 The EmoAtlas library: What are its advantages

Citing again the article “EmoAtlas: An emotional profiling tool merging psychological lexicons, artificial intelligence and network science”[9], ≪Thanks to its hybrid AI/lexicon structure, EmoAtlas does not require massive training on huge text corpora, unlike BERT and its derivative models. This makes it easier to extend EmoAtlas’ support to multiple languages besides English. In this work, we show experiments with English and Italian texts, given the expertise of the authors, but showcase and release a technical implementation of EmoAtlas supporting 18 languages≫.
Again, ≪in the task of detecting emotions in human-labelled social media posts and news media articles, either in Italian or in English, EmoAtlas achieves performances analogous, or even superior (e.g., 70.2% precision for detecting joy in tweets), to state-of-art natural languages processing techniques like BERT, RoBERTa, distillBERT, and ALBERT (e.g., 67.9% precision for detecting joy in tweets). This performance comes with EmoAtlas being 12 times faster than BERT. In a psychometric task like reproducing human creativity ratings for 1,071 short stories, EmoAtlas and BERT obtain equivalent predictive power≫.
Essentially EmoAtlas tends to guarantee better performance, in less time and with a larger possibility of language choice.

3.4 Forma Mentis Networks: What are they?

Forma Mentis Networks are a key concept necessary to truly understand how the EmoAtlas library works and the further analyses performed in this research.
In the world of cognitive science, understanding the intricate workings of the human mind has been a long-standing quest. Among the various approaches employed to unravel this puzzle, the concept of Forma Mentis Networks (FMNs) has emerged as a promising tool for mapping and analysing individual and collective mental landscapes.

At the heart of FMNs lies the notion of ”forma mentis,” a Latin term that translates to ”mindset.” As a representation of an individual’s or a group’s collective knowledge, beliefs, and opinions, FMNs capture the intricate web of concepts and their relationships that shape our thoughts and perceptions.

As explained in the article “Reviewing Theoretical and Generalizable Text Network Analysis: Forma Mentis Networks in Cognitive Science” [10] written by Oleksandra Poquet and Massimo Stella, the formation of FMNs typically involves two main approaches: Behaviorally-Derived Forma Mentis Networks (BFMNs) and Textual Forma Mentis Networks (TFMNs). BFMNs are constructed through experiments that request free associations from participants, connecting related concepts and assigning emotional valences to reflect their perceived attitudes towards those concepts. TFMNs, on the other hand, are derived from textual data, such as online conversations, social media posts, or written documents. By analysing the frequency and connectivity of words, TFMNs reconstruct the underlying mental structures that underpin the texts.

The importance of the Forma Mentis Network comes from their ability to try to replicate human cognition.
In particular in the Textual Forma Mentis Networks (since it is the type used in this research) it is relevant the completely different approach compared to the traditional technique: in this case, the focus is not on the presence/absence of a word but on the relation between them.
With this approach it is possible to identify the syntactic relationships in text and truly take into account the real meaning of a sentence.

3.5 Plutchik's wheel of emotions: What it is and how to interpret it

Another key concept necessary to truly understand how the EmoAtlas library works and the further analyses performed is the Plutchik's wheel of emotions.
The Plutchik's Wheel (see Figure 4), also known as the Emotion Wheel, was created by psychologist Robert Plutchik as a tool to understand and categorise complex emotions. It visualises the relationships between different emotions and their varying intensities, using a color-coded, wheel-like diagram.
As described by Robert Plutchik in his article called "The Nature of Emotions: Human emotions have deep evolutionary roots, a fact that may explain their complexity and provide tools for clinical practice" [11], ≪In English there are a few hundred emotion words, and they tend to fall into families based on similarity. I have found that the primary emotions can be conceptualized in a fashion analogous to a color wheel - placing similar emotions close together and opposites 180 degrees apart, like complementary colors. Other emotions are mixtures of the primary emotions, just as some colors are primary and others made by mixing the primary colors. [...] I have extended the circumplex model into a third dimension, representing the intensity of emotions, so that the total so-called structural model of emotions is shaped like a cone.
The notion of a circumplex model is not my invention, nor is it new. Social psychologist William McDougall noted the parallel between emotions and colors in 1921, writing that "the color sensations present, like the emotions, an indefinitely great variety of qualities shading into one another by imperceptible gradients...."
The first circumplex model was one developed by Brown University psychologist Harold Schlosberg in 1941, after he had asked research participants to judge the emotions posed in a standard set of pictures of facial expression. Schlosberg added the intensity dimension to his model.
My own model was proposed in 1958, when I suggested eight basic bipolar emotions: joy versus sadness, anger versus fear, acceptance versus disgust and surprise versus expectancy≫.

Essentially, Plutchik identified eight primary emotions: joy, trust, fear, surprise, sadness, anticipation, anger, and disgust. Each of these primary emotions has a polar opposite (for instance, joy is the opposite of sadness).
These emotions can also vary in intensity: the ones in the centre represent stronger levels of the primary emotion, while those further to the centre represent softer levels (for instance, the emotion of anger can range from rage to annoyance).
Several alternative models have been proposed through the years, with a number of primary emotions that range from 3 to 11, but the Plutchik's Wheel of Emotion has established itself as the benchmark in this field. One of the main reasons for its success is how easily is possible to combine different emotions to obtain a more exhaustive range of them. To clarify better this concept let's have a look at the Figure 5 taken from the article "PyPlutchik: Visualising and comparing emotion-annotated corpora" [12]. As we can see, it is possible to reach four levels of emotion combination with a total of 36 emotions (the initial 8 are included). The Plutchik's wheel of emotion is the base of EmoAtlas, the Python library used to perform the Sentiment Analysis.

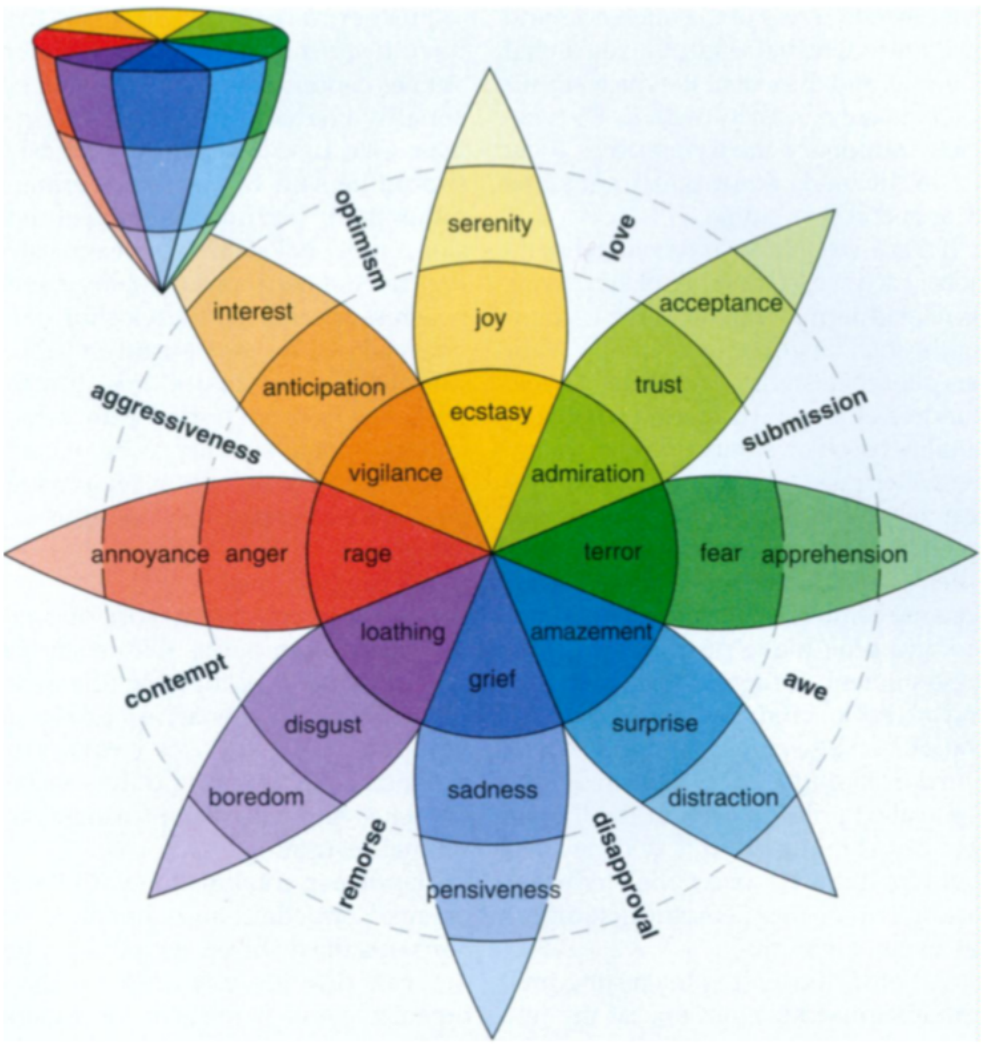

Figure 4: The Plutchik's wheel: The Plutchik's wheel of Emotions, developed by psychologist Robert Plutchik, is a circular diagram that illustrates the relationships among various basic emotions. Plutchik identified eight primary emotions: joy, trust, fear, surprise, sadness, disgust, anger and anticipation. It also represented the intensity of these emotions which change on the basis of the distance from the center. Reproduced by Plutchik 2001

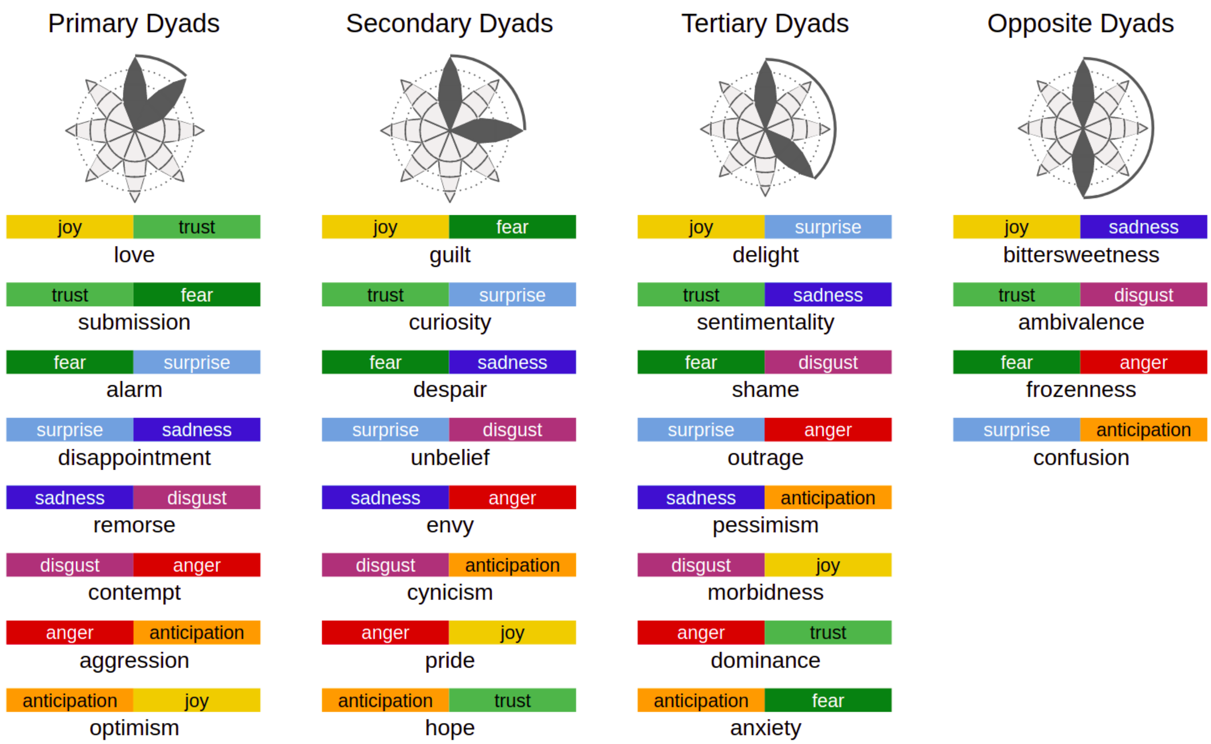

Figure 5: The Plutchik's Wheel: The model presented by Plutchik suggests that complex emotions (the so-called dyads) arise from combinations of the basic emotions. Here is a representation. Reproduced by Semeraro et al. 2021

3.6 The LOCO corpus: Description of the dataset at the base of this research

The language of conspiracy (LOCO) corpus is a collection of text data related to conspiracy theories. It is an 88-million-token corpus which contains 96,743 documents divided between Conspiracy (they are 23,937) and Mainstream (they are 72,806).
As said by the dataset's creators (Alessandro Miani, Thomas Hills and Adrian Bangerter) in their article "LOCO: The 88-million-word language of conspiracy corpus" published the 25 October 2021[8]: ≪The main goal of LOCO is to shed light on the language of conspiracy≫ and it became a resource for studying and analyzing the language, themes, and patterns present within conspiracy-related word.

But what are the differences with the existing Conspiracy theories datasets? The answer to this question is summed up in Figure 6 (Table taken from the "LOCO: The 88-million-word language of conspiracy corpus" article).

Resource	BNC	WaCky	CORPS	FNweb	RumTweet	PHEME	NYT	LOCO
Focus	Language	language	Political speeches	Fake news	Rumors	Rumors	Conspiracy	Conspiracy
Obtained from	Printed material	Web pages	Web pages	Webpages from list of websites	Twitter	Twitter	Newspaper	Webpages from list of websites
Number of documents	4 K	2.69 M	3.6 K	14 K (7 K fake)	192 K tweets (61 K rumor)	7.5 K threads (35 K rumor tweets)	100 K (800 conspiracy)	96 K (24 K conspiracy)
Number of tokens	100 M	1.9 B	7.9 M	7 M*	2.8 M*	100 K*		88 M
Topic structure	NO	2 K seeds	NO	NO	YES 111 events (60 rumors, 51 non-rumors)	YES 9 events	YES	YES 47 seeds 600 topics
Grouping structure	NO	NO	NO	YES	YES	YES (matched)	YES	YES (matched)
Year range			1917 2010	2013 2018	2006 2009	Events around 2014–2015	1897 2010	1853 2020
Freely available	YES	YES	YES	YES	YES	YES	NO	YES

Note. Resources: BNC (Aston & Burnard, 1998); WaCky (Baroni et al., 2009); CORPS (Guerini et al., 2013); FNweb (Castelo et al., 2019); RumTweet (Kwon et al., 2017); PHEME (Zubiaga et al., 2016); NYT (Uscinski et al., 2011). *Number of tokens calculated from studies' freely available datasets

Figure 6: Comparison of the main available datasets. As we can see the LOCO corpus overall performs better than the others. Reproduced by Miani et al. 2022.

The first difference with other data sources is the focus: as said before the main aim is to emphasise conspiracy texts and not to concentrate on a specific topic (such as politics) like other data sources have done (for instance the CORPS one).
The source has another distinguishing feature from the others. While social media platforms like Facebook, Twitter, and Instagram attract more traffic, websites offer more comprehensive narratives than social media posts. Specifically dedicated to developing, collecting, and spreading conspiracy theories, conspiracy websites provide space to discredit official narratives and serve as reliable sources for conspiracy theories believers, but they allow also to understand better what these people believe. The analysis of conspiracy webpages instead of social media metadata has a principal advantage: these webpages have structured texts inside them, which are accompanied by their metadata, facilitating the data extraction

and the study of the text content.
As reported in the same article [8], other existing corpora, like the WaCky corpus and the British National Corpus, do not focus on a specific source type or topics, and this does not allow the unambiguous identification of conspiracy-related content.
Citing again the article: ≪Other corpora focus on specific themes. In the field of online anti-vaccine movements, a few studies have collected webpages gathered through search engines (Fu et al., 2016; Okuhara et al., 2017; Sak et al., 2015). This approach is convenient, as it allows researchers to obtain data by mimicking how users retrieve information. However, because these corpora were collected manually, sample sizes are limited, therefore reducing generalizability≫ [8].
Also the year range plays a key role since in some cases it is restricted to only a few years. For instance, in the FNweb dataset, the year range goes from 2013 to 2018. The same thing can be said for the RumTweet (2006 - 2009) and the PHEME (2014 - 2015) corpus which extends their range only to a few years.
In response to the limitations of existing corpora, the LOCO corpus has been introduced, allowing us to examine the evolution and impact of conspiratorial beliefs across different media sources and platforms.

The construction of the dataset is based on seeds (keywords) used to retrieve the webpages from which to extract the texts [8].
The seeds selection has been done by extracting them from the items of two conspiracy theory-based surveys: a national poll (Jensen, 2013, Source 1, e.g., "Do you believe that Lee Harvey Oswald acted alone in killing President Kennedy, or was there some larger conspiracy at work?") and the 17th "endorsement of conspiracy theories" from Douglas and Sutton (2011, Source 2, e.g., "The American moon landings were faked"). This is because as said in the article[8]: ≪We extracted the seeds from these surveys for two reasons. Firstly, these surveys on conspiracy theories encompass a broad set of well-known CTs, since they are supposed to measure specific beliefs from a wide range of people.
Secondly, these surveys condense each theory within a short space, usually a sentence. These two surveys were chosen because, while they measure specific theories, they are broad in scope, and encompass a large and heterogeneous set of conspiracy theories.≫
Other 20 seeds have been added to the selection to make it more complete with other popular (e.g., Illuminati, genetically modified organisms, Pizzagate) and current (e.g., coronavirus, Bill Gates, 5G) conspiracy theories keywords missing from the first and the second source.

The other important selection at the basis of the LOCO creation is the website choice.
Citing again the "LOCO: The 88-million-word language of conspiracy corpus" article[8], the filtering has been done following this process.
≪We gathered a list of conspiracy websites from mediabiasfactcheck (MBFC). Websites are labelled by MBFC as conspiracy if they publish unverifiable information related to known conspiracies such as the New World Order, Illuminati, false flags, aliens, anti-vaccination propaganda, etc. (for further details, see category descriptions in the "Website category" section). From the whole list of 241 conspiracy websites, we selected (in December 2019) those that scored the highest on the conspiracy rating (i.e., "tin foil hat," N=68). This increased the chances of obtaining highly conspiratorial texts, limiting contamination by mainstream or less conspiratorial texts.
The mainstream list of websites was created (in June 2020) in a data-driven fashion by

extracting the websites returned by Google for each seed. While maximizing data acquisition, this approach also mimics users' online behaviour. We proceeded as follows. For each seed, we created a Google query, gathered the resulting top 40 URLs, and extracted the websites' domains.Footnote5 We repeated this operation with different IPs, mimicking the searches from the UK (London), USA (New Jersey), and Australia (Melbourne) to maximize English language domains as well as the heterogeneity of websites. This procedure returned a total of 1453 unique domains. All domain counts were aggregated, and we computed two popularity metrics per domain: (1) the number of times a domain appears overall for all seeds (absolute frequency), and (2) the number of unique seeds associated with a specific domain (relative frequency). These two metrics were chosen to obtain a large portion of pages (absolute method) and a wide coverage of seeds (relative method). The top 120 domains for each metric were visually inspected to remove potential conspiracy websites (none appeared), less relevant websites such as those not related to text content (YouTube, Amazon, Instagram, Pinterest, LinkedIn, Shutterstock), websites with user-generated content (Blogger, Facebook, Twitter), and other websites such as those related to movie reviews, private companies, and online courses. Following these exclusion criteria, a total of 19 domains were removed. Keeping all domains appearing in both metrics (N=135), this list was visually inspected and subdomains were aggregated (e.g., keith.seas.harvard.edu, sitn.hms.harvard.edu, health.harvard.edu, hsph.harvard.edu aggregated to harvard.edu) while removing mistakenly extracted domains (e.g., www) and non-English domain suffixes (e.g., nationalgeographic.fr). This left us with 93 domains.»

After the authors obtained both the list of the seeds and the one of the website they did a final step of text extraction.
Having the URL list of websites containing the keywords, it is possible to perform a text extraction using the Python Goose package.
Further cleanings have been performed, removing:

- the text where the language was not set as English;
- the empty documents;
- the duplicated texts;
- the texts shorter than 100 words.

It is important to underline how seeds are not a proxy of topics.
Even if seeds have been used to find the webpages from which the text has been extracted, this doesn't mean that the keywords are their main topic: they can appear in some links, comments, as well as in boilerplate texts inside the site. Take for instance the seed manually added of "5g". This can be present inside the documents both because it is discussed inside the main text and because there is an advertisement with a link that contains that word.
This is the reason why the authors also provide a classification of the different documents based on the Latent Dirichlet Allocation (LDA). This algorithm family is an unsupervised probabilistic machine learning model which allows identifying co-occurring word patterns and extracting the underlying topic distribution for each text document. It is necessary to set a priori the number of topics needed, and in this case, the creators have chosen to divide the documents between three options: 100, 200 or 300 topics.
The higher the number of topics the higher the specificity of the topic will be, but, at the same time, the computational cost and the complexity of the model will increase with it.

In this particular case the authors choose to use the LDA with the Gibbs sampling. This type of sampling is used to cover the so-called posterior inference which is the task of estimating the posterior distribution of the hidden variables given the observed data. Citing the article ”A Theoretical and Practical Implementation Tutorial on Topic Modeling and Gibbs Sampling” [13] ≪Gibbs Sampling is one member of a family of algorithms from the Markov Chain Monte Carlo (MCMC) framework. The MCMC algorithms aim to construct a Markov chain that has the target posterior distribution as its stationary distribution. In other words, after a number of iterations of stepping through the chain, sampling from the distribution should converge to be close to sampling from the desired posterior.≫
A simplified version of the Gibbs sampling process in LDA can be described as follows:

1. Initialize the topic assignments for each word in the corpus randomly.
2. For each word in each document, do the following:
    - Remove the current topic assignment from the count matrices.
    - Calculate the conditional distribution of the topic given the word and the remaining topics.
    - Sample a new topic from this distribution.
    - Increment the count matrices corresponding to the new topic assignment.
3. Repeat the above steps until convergence.

3.6.1 The LOCO corpus: the problems of this dataset

Even if this corpus is the largest corpus of conspiracy theories available and it has all the advantages explained above, there are also some challenges related to the data that the analysts have faced.

- One of the primary issues is related to the average length of conspiracy documents, which is significantly higher than the one of mainstream documents. This difference in document length might introduce biases in analyses and interpretations, potentially skewing the results towards or against certain document categories due to their extended or abbreviated nature.
- The second main challenge is the absence of balance in document numerosity between the two groups of documents.
  With approximately one-fourth of the documents attributed to conspiracy sources and the remaining three-fourths representing mainstream sources, this unequal distribution raises concerns about the proportional representation of different points of view and narratives, possibly impacting the dataset's overall reliability and inclusivity.
- Lastly they faced the problem related to the distribution of topics and seeds across the documents. There is a lack of uniformity in the number of documents assigned to one side or another, leading to potential challenges in achieving a balanced and comprehensive coverage of various themes and subjects. The uneven distribution of these elements could influence the dataset's comprehensiveness and results.

3.6.2 The LOCO corpus: How the researchers of the ScienceAdvances article have faced these issues

As explained in the previous Chapters, the ScienceAdvances article ”Interconnectedness and (in)coherence as a signature of conspiracy worldviews” [7] is based on the LOCO corpus. Since they also faced the same problems related to the dataset, the way they handled them can be taken as a benchmark.
The chosen approach is to create several subsets by facing one problem at a time and then to replicate the metrics and the tests performed for each one of these.
Six different corpora have been created:

- three matched for topics;
- three matched for the word count.

Starting from the ones matched for topics, the researchers aimed to find a subset of topics discussed by both conspiracy and non-conspiracy documents.
Their goal was to maintain an approximate balance (around a 0.50 ratio) between conspiracy and non-conspiracy documents within each topic, ensuring parity across various subject matters. For each individual document, the researchers start the process by extracting the predominant topic (from the 200 topics found with the LDA classification) identified by the highest gamma value. In this way, they can establish which is the representative theme inside each document.
Following this, the researchers computed the ratio of conspiracy and non-conspiracy documents for each topic.
Topics that displayed significant deviation from the target of 0.50 ratio (approximately equal representation of conspiracy and non-conspiracy documents) were excluded from further analysis. For instance, topics with imbalanced ratios such as 0.10 conspiracy and 0.90 non-conspiracy were omitted due to the fact that the topics show a considerable asymmetry in the presence of conspiracy or non-conspiracy documents.
To ensure a balanced representation of documents across topics within each subcorpus, the researchers used three distinct windows centred around the 0.50 ratio. These windows were:

- C1 = 0.50 ± 0.20 (ratio within 0.30 and 0.70, the corpora include 18,512 documents, 7,819 conspiracy and 10,693 non-conspiracy);
- C2 = 0.50 ± 0.10 (ratio within 0.40 and 0.60, the corpora include 4,186 documents, 2,090 conspiracy and 2,096 non-conspiracy);
- C3 = 0.50 ± 0.05 (ratio within 0.45 and 0.55, the corpora include 1,490 documents, 745 conspiracy and 745 non-conspiracy).

For the corpora matched for the word count, the primary aim was to procure subsets of both conspiracy and non-conspiracy documents while ensuring parity in terms of word count. Three distinct document lengths—medium, long, and short—were intentionally selected.
The corpus C4 contains the selection of medium-length documents.
To obtain it, the analysts filtered all the documents keeping only the ones with a length ranging $\pm$ 0.2 the standard deviations value (SD) with respect to the mean value of LOCO’s document length (912 words). Precisely, the range goes between 700 and 1,124 words.
The selection of 0.2 SD (in contrast to, for instance, 0.5 or 1 SDs) was an arbitrary choice made after several experiments and was selected because it resulted in documents

that exhibited no statistically significant differences in length between conspiracy and non-conspiracy documents.
Corpus C4 comprehends a total of 19,944 documents (with 5,077 conspiracy and 14,867 non-conspiracy).

Moving to the following corpus (called corpus C5) the focus was on long-length documents characterised by extensive textual content. The documents selected are the ones falling within a range of ± 0.1 SDs around 1 SD above the mean of LOCO's document length (1,971 words). The covered word counts fall between 1,865 and 2,077 words.
Corpus C5 comprehends a total of 1,497 documents (with conspiracy = 675; non-conspiracy = 822).

The last corpus created (C6) emphasis was on short-length documents.
The documents falling within a range of ± 0.1 SDs around 1 SD below the mean value (i.e., 383 words) of LOCO's document length were selected. In this way, the corpora contain the document with a word count between 277 and 489 words. However, due to the resulting data imbalance (the conspiracy documents are 3,624 while the non-conspiracy are 17,120), the researchers decided to randomly sample 1,000 documents from each subcorpus.
The result is a total of 1,843 distinct documents, with 865 conspiracy and 978 non-conspiracy documents.

3.7 Topic selection: a step taken before starting the analyses

As said in the previous chapters, my analysis will be performed on the LOCO corpus, and for this reason, I have also faced some challenges related to the dataset composition. To overcome these challenges some decisions have been taken.

The first main issue faced regarding the choice of the number of topics to take as a benchmark for the LDA classification: 100, 200 or 300?
To understand the importance of this choice there is the need to have an idea of how a different numerosity of topic can influence their specificity.
The additional material of the article "LOCO: The 88-million-word language of conspiracy corpus"[8] contains a particular study on this subject, underlining the importance of this choice to allow the topics to capture the real text matter.
Going deeper, they prove the existence of a positive correlation between higher 'k' values (representing a larger number of topics within the corpus) and the increase in topic resolution. Conversely, lower 'k' values also mean a more general topic.
For example, when analysing the topics relating to the disappearance of flight MH370, specifically referred to as topics k100_51, k200_142 and k300_272, can be noticed a progression in the specificity of the topics concerning 'k'.
It is possible to see the detailed data extraction from the supplementary file topic_description.json related to this topic (extraction taken from the additional material of the article "LOCO: The 88-million-word language of conspiracy corpus"[8]) in Figure 7.
In this data extraction, we can find:

- Topic ID: the topic indexed as the sequential topic ID preceded by the k value, so for example "k100_4" refers to the fourth topic extracted with k = 100.
- Top 15 words: the top 15 words of the topic are ordered by decreasing beta weight.
- N (C/M): The total (N) number of documents whose such topic has the max gamma value across all topics within a k set. N_C and N_M refer to the number of documents within conspiracy and mainstream subcorpora. The variable "Prop conspiracy" refers to the proportion of conspiracy documents.
- Topic in K r: It reports the topic with the highest correlation among all topics within the k set. The correlation is computed on the document level (N = 96,743).
- Topic all r: same as above, but the correlation is computed for all topics for all k sets (i.e., N = 600) on the document level (N = 96,743).
- LF r: the highest correlation with lexical features (LF) from Empath (E) and LIWC (L).

As we will see, this information (in particular the Top 15 words and the Lexical Feature) will be crucial to the analysis done in the supplementary material.

Going back to our analysis, the keyword "mh370" shifts from its 15th position in k100 to the 6th position in k200 and further advances to the 4th position in k300. This shift means an increase in the beta value for the term and its increasing significance within the topic. Essentially, as "k" increases from k100 to k300, the description of the MH370 disappearance becomes more precise, shifting its focus from generic flights to the specific incident.

Table S12 – Topic description: MH370

K_Topic	Top 15 words	N C	N M	Max Topic	r	Max LF	r
k100_51	*plane, flight, search, airlin, aircraft, air, pilot, passeng, malaysia, crash, ocean, miss, fli, found, mh370*	144	1074	Topic_091	0.07	E_air_travel	0.63
k200_142	*search, plane, malaysia, flight, ocean, mh370, miss, disappear, airlin, found, malaysian, investig, debri, indian, aircraft*	55	886	Topic_123	0.19	E_air_travel	0.5
k300_272	*search, plane, malaysia, mh370, ocean, flight, miss, malaysian, disappear, found, airlin, investig, indian, debri, area*	48	847	Topic_187	0.21	E_air_travel	0.49

Figure 7: Table extracted from the topic_description.json file, keeping only the Topic related to the MH370 flight disappearance. Reproduced by Miani et al. 2022.

Additionally, the count of documents where this is the top topic (that means possessing a higher gamma value across all topics within the 'k' dataset) diminishes with higher "k", indicating an augmented level of specificity.

The correlations with the general lexical feature of air_travel decrease with the increase of k, suggesting that the topic is less general, focusing less on air_travel and more specifically on MH370 disappearance.

Lastly in Figure 8, the gamma values of all documents are depicted across a temporal span from 1995 to 2020, specifically focusing on the three topics linked to the MH370 flight disappearance. Topics exhibiting lower noise (i.e., lower gamma values) preceding the event on March 8th, 2014, are regarded as more specific in nature. Also in this case the group with a higher number of topics highlights higher specificity and precision in matching the document's argument.

Figure S4 – The same topic over time on different ks

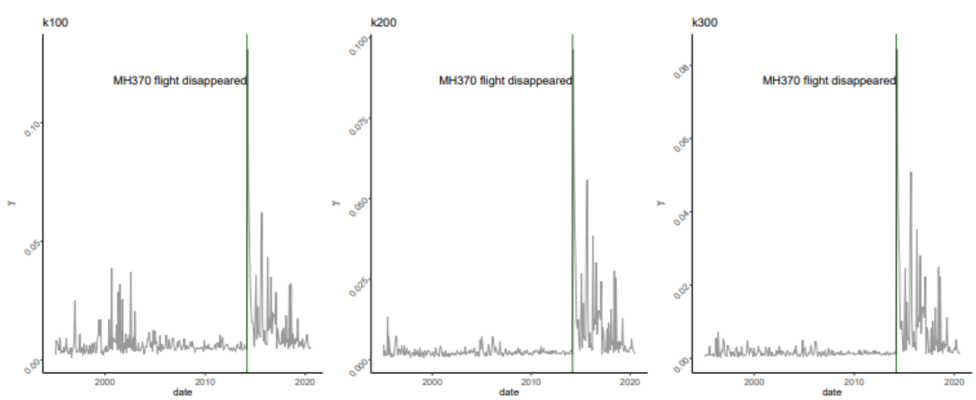

Figure 8: Figure extracted from the additional material of the ScienceAdvances article. It shows the MH370 disappearance discussion over the time in the difference ks. Reproduced by Miani et al. 2022.

For the reason explained above, I decided to go with the set of topics k300.
In this way there is a higher probability of not mixing documents that treat similar topics but that are not equal to each other (for instance air travel and the flight MH370 disappearance or Lady Diana's death and the British Royal Family).
If not, this overlap between similar but non-identical topics can influence the analysis and truthfulness of my conclusion.

Another point of interest is the presence of topics not equally distributed between the conspiracy and the mainstream side.
Arguments discussed by only one of two sides or discussed by only a few of one side can

strongly influence the results and create bias. What I want is to take into consideration only the subjects with equal participation, since they can be used to compare how the two side face certain topic.
To do it I replicated the approach followed in the ScienceAdvances article and I filtered the documents keeping only the ones with a distribution rate between conspiracy and mainstream of 0.50 ± 0.05 (range between 0.45 and 0.55, with 3,361 documents, 1,689 conspiracy and 1,672 mainstream). I keep only the stricter selection used by the ScienceAdvances article researcher to be sure to not have the issues described above.

Lastly, there is the problem related to the different text lengths of the documents.
In this case I decided to not take any action against this problem because my research will be based on the so-called Forma Mentis Networks.
As explained in the article "Forma mentis networks quantify crucial differences in STEM perception between students and experts"[14] written by Massimo Stella, Sarah de Nigris, Aleksandra Aloric, Cynthia S. Q. Siew, Forma Mentis Networks (FMNs) are a new approach to map the mindset or "forma mentis" of individuals or groups. These networks consist of words as nodes, each with a valence attribute (i.e., positive, negative, or neutral), and free associations as links. The networks aim to capture the associative structure of semantic memory and provide a quantitative measure of how concepts relate to each other in a person's mind.
This particular network structure is not affected by differences in text length because it is based on the strength and frequency of associations between concepts, rather than on the absolute number of words. This means that a longer text will simply have more opportunities for connections to be formed between concepts.
For example, consider the concepts "cat" and "dog." In a short text, the two concepts may only be connected once or twice. However, in a longer text, they may be connected dozens of times. This increased exposure will lead to stronger and more frequent associations between the two concepts, which will be reflected in the FMN.

3.8 The Text Structure Analysis: How it has been done and which metrics have been used

Let's start to go deeper into the analysis that I perform.
The first goal of my research is to verify if, with the use of the Forma Mentis network, I will get the same conclusion obtained by the researchers in the ScienceAdvances article.
To do it, I compute different indexes on the Forma Mentis network obtained from each document and then check for each topic if there is effectively a difference between the conspiracy texts and the mainstream ones.
Since Forma Mentis Networks are networks, they can be treated by applying the concepts of network science (see Haim and Stella 2023) [15]. This is the reason why the metrics chosen to reveal the characteristics of Forma Mentis Networks obtained are not specifically dedicated metrics but are also used in many other fields.
Here's an overview of the selected ones:

- Diameter of the GCC (Giant Connected Component): It represents the maximum distance between any two nodes within the network. In the context of the LOCO network, this metric quantifies the longest possible path between any two words. A large diameter suggests that the network is highly dispersed, with words spread across multiple interconnected clusters. On the contrary, a small diameter implies a more connected network where words are relatively closer together.
- Average shortest path length of the GCC: This metric, also known as the average geodesic distance, measures the average number of steps required to connect any two nodes in the network. For the LOCO network, this metric reflects the overall efficiency of information diffusion. A low average shortest path length indicates that words are well-connected and information can spread rapidly across the network. In contrast, a high average shortest path length suggests that the network is more fragmented, with information dissemination encountering more obstacles.
- Clustering coefficient of the GCC: It quantifies the tendency of nodes in the network to form densely connected clusters. In the LOCO network, this metric reflects the cohesiveness of word communities. A high clustering coefficient implies that words tend to cluster together, forming tightly knit groups of semantically related terms. On the other hand, a low clustering coefficient suggests that words are more dispersed and loosely connected.
- Degree assortativity coefficient for the GCC: This coefficient measures the tendency of similar nodes to connect. In the LOCO network, this metric reflects the homogeneity of word associations. A positive degree assortativity coefficient indicates that words with similar meanings tend to form strong connections. Conversely, a negative degree assortativity coefficient suggests that words with dissimilar meanings are more likely to be linked together.

Knowing which will be the key indicator computed, it remains to be established in which way I am going to compare the result between the conspiracy and mainstream sides for each topic.
To make an effective comparison there is the need of a statistical test.
In this way we will make our results objective and replicable.
There is also the necessity that the test chosen would be no-parametric since we don't know

a priori the distribution function of the index computed for the two categories. We neither know if these distribution changes between the conspiracy and mainstream or from one topic to another.
Indeed, a non-parametric test is a statistical method used when the data being analysed does not meet the assumptions of parametric tests, such as a normal distribution of the data, or when the sample size is small.
Another characteristic of these tests is their robustness against outliers. Parametric tests can be sensitive to extreme values or data that don't fit the expected pattern, while non-parametric tests are less influenced by such outliers.
After carefully analysing several statistical tests, I considered the Mann-Whitney U to be the best in this case.
The Mann-Whitney U test, as defined in the website article "Mann-Whitney U Test: Assumptions and Example" written by Elliot McClenaghan and published by the Technology Networks[16], ≪is a non-parametric statistical test used to compare two samples or groups. The Mann-Whitney U Test assesses whether two sampled groups are likely to derive from the same population, and essentially asks; do these two populations have the same shape with regard to their data? In other words, we want evidence as to whether the groups are drawn from populations with different levels of a variable of interest.
It follows that the hypotheses in a Mann-Whitney U Test are:

- The null hypothesis (H0) is that the two populations are equal;
- The alternative hypothesis (H1) is that the two populations are not equal.≫[16]

Even this test has some key assumptions at base of it. In particular the two groups must be composed by continuous variable and the the data should comes from two randomly selected independent samples (meaning the groups must have no relationship between each other) [16].

Despite its strengths, it is important to note that the Mann-Whitney U test has some limitations. For instance, it does not provide information about the size of the difference between groups or how the groups differ in terms of means or medians: it only assesses whether there's a difference.
To overcome this problem and be able to understand which of the two sides tends to have higher values compared to the other, in the case of rejection of the null hypothesis I decide to compute also the Hodges-Lehmann Estimate.
This measure, also known as the pseudo-median, is a robust (meaning that it is relatively insensitive to outliers) and nonparametric estimator of a population's location parameter. For two samples, the Hodges–Lehmann estimator is defined as the median of the differences between each possible pair drawn from the two samples and it agrees with the median for symmetric data-sets or populations.

Now, let's further clarify the steps followed for each topic:

1. The first step is to compute the metrics for all the documents.
2. Afterwards I compute the Mann-Whitney U statistical test to test the two metrics distribution (one for the conspiracy and one for the mainstream) to verify if they come from the same population (null hypothesis).
3. If we accept the null hypothesis then I assign the "C $\sim$ M" in the Result column of the

new table created.

4. If we reject the null hypothesis we check the output of the Hodges–Lehmann estimator:
5. If it is positive we assign “C > M” in column Result.
6. If it is negative then the Result will be “C < M”.
7. Then, computing the weighted frequency, let’s draw conclusions at a high level.

Knowing these steps is also easy to understand the table’s output of my analysis.
This table contain in this order:

- Topic_ID: it’s the topic identification number from the k300 LDA output. As said before, these topics are filtered keeping only the only with a rate of conspiracy and mainstream that range between 0.45 and 0.55.
- N, N_C, N_M: these columns contain the number of documents inside the topic, the number of documents which are conspiracy and the number of the mainstream ones.
- Prop_Conspiracy: is the proportion of conspiracy documents compared to the total number.
- pvalue: is populated with the p-value of the Mann-Whitney U test.
- *_sign_lev (where instead of the asterisk there is the name of the calculated index): is the significance level assigned to the test output on the base of the pvalue:
  - “-” if it is higher than 0.05;
  - “*” if it ranges between 0.05 and 0.01;
  - “**” if it ranges between 0.01 and 0.001;
  - “***” if it is lower than 0.001.
- *_result (where instead of the asterisk there is the name of the calculated index): tell us if the null hypothesis is rejected (“REFUSE”) or not (“ACCEPTED”).
- HL_difference_estimate: it’s the Hodges-Lehmann Estimate and becomes crucial in the case of rejection of the null hypothesis to understand which of the two sides tends to have bigger value.
- Result: it tells us the final output of this analysis for that specific topic. It can assume these possible value:
  - “C $\sim$ M”: we accepted the null hypothesis so we can say that there are no significant differences between the output of the metric computed for both the side;
  - “C > M”: we accepted the alternative hypothesis and the Hodges-Lehmann Estimate is positive so we can say that the metric compute for the conspiracy side tends to higher compared to the mainstream one;
  - “C < M”: we accepted the alternative hypothesis and the Hodges-Lehmann Estimate is negative so we can say that the metric compute for the conspiracy side tends to lower compared to the mainstream one.

3.8.1 The Text Structure Analysis - The results obtained: Diameter

As said above, the diameter is the maximum distance between any two nodes within the network and it can be useful to understand the degree of connection between nodes (a small diameter suggests that the network nodes are relatively closer together while a higher value means they are less interconnected between each other).
Looking at the results obtained and shown in Figure 9 can be seen that (analysing the distribution at a basic level) the topics where the conspiracy documents diameter surpasses the mainstream ones constitute 28.57% (4 out of 14 topics) of the total. Conversely, there are no cases where the conspiracy diameter is lower than the mainstream one, making up 0.0% of the observed topics. Lastly, the majority, standing at 71.43% (10 out of 14 topics), exhibit a balance where conspiracies metrics are approximately equivalent to the mainstreams.
The problem with this analysis is that it does not take into account the topic composition. To avoid this issue I decided to also compute the weighted frequency. In this way also the document numerosity will be taken into account. Indeed, Weighted frequency is a method used to determine how often an item appears within a dataset, taking into consideration the importance or value of each item. Unlike simple frequency counts, which assign equal weight to every instance, weighted frequency allows items to be weighted by relevance, which in this case is equal to the topic numerosity.
With this new metric the results change significantly: the topics where conspiracy diameter exceeds the mainstream have a weighted frequency of 0.5126, emphasising their significance within the dataset. This means that the larger number of documents within topics with "C > M" has a greater impact on the overall conclusion drawn from the weighted frequency analysis.
Let me explain better.
If we consider the count of topics, it seems like most topics favour "C $\sim$ M" (conspiracy and mainstream sources come from the same population). However, when we weigh the results with the frequency of documents within each topic, topics where "C > M" (conspiracy sources differ from mainstream sources and tend to have higher Z-score) have a larger influence due to their larger document count. As a result, the overall conclusion shifts towards "C > M", indicating that despite fewer topics showing this result, the larger number of documents within them impacts the overall assessment resulting in a higher relevance.
Going further with the results analysis, topics where C is less than mainstream have a weighted frequency of 0.0, highlighting their absence or negligible presence in this context. Meanwhile, topics showing an equal distribution between conspiracy and mainstream have a weighted frequency of 0.4874.
As we can see there is a strong difference in the impact of the "C > M" and this implies a tendency to have fewer connections between the nodes in the conspiracy networks.

	Topic_ID	N	N_C	N_M	Prop_conspiracy	pvalue	Diameter_sign_lev	Diameter_result	HL_difference_estimate	Result
0	k300_3	89	42	47	0.4719	7.123666e-01	-	ACCEPT	0.000028	C ~ M
1	k300_11	218	119	99	0.5459	7.947661e-01	-	ACCEPT	-0.000052	C ~ M
2	k300_12	229	117	112	0.5109	3.697575e-01	-	ACCEPT	0.000058	C ~ M
3	k300_37	214	99	115	0.4626	3.993050e-06	***	REFUSE	0.999951	C > M
4	k300_84	456	246	210	0.5395	5.925141e-06	***	REFUSE	0.000011	C > M
5	k300_98	43	21	22	0.4884	9.704615e-01	-	ACCEPT	0.000057	C ~ M
6	k300_108	53	28	25	0.5283	6.024074e-01	-	ACCEPT	0.000003	C ~ M
7	k300_121	77	38	39	0.4935	3.375279e-01	-	ACCEPT	0.000006	C ~ M
8	k300_140	706	350	356	0.4958	6.099698e-14	***	REFUSE	0.999969	C > M
9	k300_147	144	73	71	0.5069	6.201914e-01	-	ACCEPT	-0.000033	C ~ M
10	k300_191	347	187	160	0.5389	3.748039e-04	***	REFUSE	0.000040	C > M
11	k300_210	224	103	121	0.4598	1.870308e-01	-	ACCEPT	0.000049	C ~ M
12	k300_222	459	217	242	0.4728	8.846123e-01	-	ACCEPT	0.000044	C ~ M
13	k300_293	102	49	53	0.4804	2.215230e-01	-	ACCEPT	0.000059	C ~ M

Figure 9: Diameter: Results representation for each topic considered

Proportion of topic by possible result:

- The topics with "C > M" are 4 / 14 (28.57 %)
- The topics with "C < M" are 0 / 14 (0.0 %)
- The topics with "C $\sim$ M" are 10 / 14 (71.43 %)

Topic result with the relative weighted frequency:

- "C > M" has a weighted frequency of 0.5126
- "C < M" has a weighted frequency of 0.0 *
- "C $\sim$ M" has a weighted frequency of 0.4874

* In this case, the weighted frequency is 0 because there is no topic with that results prevalence. It follows that one number (number of documents inside the topics) multiplied by 0 (number of topics with that results prevalence) would be equal to 0.

3.8.2 The Text Structure Analysis - The results obtained: Average shortest path length

The average shortest path length is a measure of the average number of steps required to connect any two nodes in the network.
A high value means that the words are not so well connected to each other (since on average require more steps to pass from one node to another) while a low value means the opposite. Looking at our results (Figure 10) we notice that the topic where we have differences on these metrics are exactly the same where we had delta in the previous metric.
All the considerations obtained will remain the same like the fact that there is a tendency in the conspiracy documents to have less connection between each node.

	Topic_ID	N	N_C	N_M	Prop_conspiracy	pvalue	ASPL_sign_lev	ASPL_result	HL_difference_estimate	Result
0	k300_3	89	42	47	0.4719	3.725463e-01	-	ACCEPT	0.058071	C ~ M
1	k300_11	218	119	99	0.5459	3.754135e-01	-	ACCEPT	-0.041267	C ~ M
2	k300_12	229	117	112	0.5109	2.262038e-01	-	ACCEPT	0.040978	C ~ M
3	k300_37	214	99	115	0.4626	2.195989e-09	***	REFUSE	0.224639	C > M
4	k300_84	456	246	210	0.5395	2.305167e-10	***	REFUSE	0.151435	C > M
5	k300_98	43	21	22	0.4884	6.013961e-01	-	ACCEPT	-0.110599	C ~ M
6	k300_108	53	28	25	0.5283	8.237552e-01	-	ACCEPT	-0.015227	C ~ M
7	k300_121	77	38	39	0.4935	3.564877e-01	-	ACCEPT	0.066236	C ~ M
8	k300_140	706	350	356	0.4958	1.680989e-22	***	REFUSE	0.186050	C > M
9	k300_147	144	73	71	0.5069	8.824621e-01	-	ACCEPT	0.005560	C ~ M
10	k300_191	347	187	160	0.5389	4.183876e-04	***	REFUSE	0.091883	C > M
11	k300_210	224	103	121	0.4598	3.929086e-01	-	ACCEPT	0.037077	C ~ M
12	k300_222	459	217	242	0.4728	4.206758e-01	-	ACCEPT	-0.016939	C ~ M
13	k300_293	102	49	53	0.4804	5.373290e-02	-	ACCEPT	0.107772	C ~ M

Figure 10: Average shortest path length: Results representation for each topic considered

Proportion of topic by possible result:

- The topics with "C > M" are 4 / 14 (28.57 %)
- The topics with "C < M" are 0 / 14 (0.0 %)
- The topics with "C ∼ M" are 10 / 14 (71.43 %)

Topic result with the relative weighted frequency:

- "C > M" has a weighted frequency of 0.5126
- "C < M" has a weighted frequency of 0.0 *
- "C ∼ M" has a weighted frequency of 0.4874

* In this case, the weighted frequency is 0 because there is no topic with that results prevalence. It follows that one number (number of documents inside the topics) multiplied by 0 (number of topics with that results prevalence) would be equal to 0.

3.8.3 The Text Structure Analysis - The results obtained: Clustering coefficient

The clustering coefficient (Figure 11) quantifies the degree to which nodes in a network tend to cluster together. It calculates the likelihood that two nodes that are connected to the same node are also connected to each other. A higher clustering coefficient indicates a higher tendency for nodes to form tightly knit clusters or communities.
Looking at the output at a topic level, it becomes evident that, among the 14 topics assessed, there is an equal partition between the cases where the clustering coefficient is equal between the two classes or it is higher in the mainstream one.
Like I have done before I perform this analysis by looking also at the weighted frequency and what I get is that the "C < M" situation (0.6486) is much more spread around the document's Forma Mentis network compared to the "C ∼ M" (0.3514).
Essentially, this means that there is a higher tendency in the Mainstream text to create strictly linked clusters.

	Topic_ID	N	N_C	N_M	Prop_conspiracy	pvalue	Clustering_coef_sign_lev	Clustering_coef_result	HL_difference_estimate	Result
0	k300_3	89	42	47	0.4719	1.081139e-01	-	ACCEPT	0.016817	C ~ M
1	k300_11	218	119	99	0.5459	5.189472e-06	***	REFUSE	-0.031189	C < M
2	k300_12	229	117	112	0.5109	2.145800e-05	***	REFUSE	-0.028490	C < M
3	k300_37	214	99	115	0.4626	9.894005e-01	-	ACCEPT	-0.000131	C ~ M
4	k300_84	456	246	210	0.5395	8.218313e-02	-	ACCEPT	0.006608	C ~ M
5	k300_98	43	21	22	0.4884	6.013961e-01	-	ACCEPT	-0.010888	C ~ M
6	k300_108	53	28	25	0.5283	2.504639e-01	-	ACCEPT	-0.013088	C ~ M
7	k300_121	77	38	39	0.4935	3.037995e-02	*	REFUSE	-0.020040	C < M
8	k300_140	706	350	356	0.4958	6.771291e-16	***	REFUSE	-0.028901	C < M
9	k300_147	144	73	71	0.5069	5.642601e-06	***	REFUSE	-0.043904	C < M
10	k300_191	347	187	160	0.5389	6.059992e-03	**	REFUSE	-0.012961	C < M
11	k300_210	224	103	121	0.4598	9.472210e-01	-	ACCEPT	-0.000437	C ~ M
12	k300_222	459	217	242	0.4728	3.330028e-09	***	REFUSE	-0.027616	C < M
13	k300_293	102	49	53	0.4804	4.062366e-01	-	ACCEPT	-0.009810	C ~ M

Figure 11: Clustering coefficient: Results representation for each topic considered

Proportion of topic by possible result:

- The topics with "C > M" are 0 / 14 (0.0 %)
- The topics with "C < M" are 7 / 14 (50.0 %)
- The topics with "C ∼ M" are 7 / 14 (50.0 %)

Topic result with the relative weighted frequency:

- "C > M" has a weighted frequency of 0.0*
- "C < M" has a weighted frequency of 0.6486
- "C ∼ M" has a weighted frequency of 0.3514

* In this case, the weighted frequency is 0 because there is no topic with that results prevalence. It follows that one number (number of documents inside the topics) multiplied by 0 (number of topics with that results prevalence) would be equal to 0.

3.8.4 The Text Structure Analysis - The results obtained: Degree assortativity coefficient

Lastly, the degree assortativity coefficient (Figure 12). It measures the tendency of similar nodes to connect. Since our texts are composed of text, it quantifies the tendency to homogeneity in the word association.
A positive degree assortativity coefficient indicates that words with similar meanings tend to form strong connections.
The output shows how (at a topic level), out of the 14 topics under analysis, 50.0% (7 out of 14) exhibit a higher value for the conspiracy side compared to the mainstream one ("C > M"). Conversely, only 7.14% (1 out of 14) of conspiracy topics demonstrate a value lower than the opposite side ("C < M"). 42.86% (6 out of 14) of the topics present a situation where conspiracy and mainstream documents present similar coefficients ("C ∼ M").
Moving to the weighted frequency we notice how in this case the order of the most spread type of result does not change taking into account the number of documents. What changes is the proportion assigned to each one of the three categories?
Now we have 0.6525 for the "C > M", 0.0649 for the "C < M" and 0.2827 for "C ∼ M".

	Topic_ID	N	N_C	N_M	Prop_conspiracy	pvalue	Assortativity_coef_sign_lev	Assortativity_coef_result	HL_difference_estimate	Result
0	k300_3	89	42	47	0.4719	6.384144e-02	-	ACCEPT	0.027966	C ~ M
1	k300_11	218	119	99	0.5459	4.154665e-03	**	REFUSE	-0.032744	C < M
2	k300_12	229	117	112	0.5109	5.761704e-02	-	ACCEPT	0.017310	C ~ M
3	k300_37	214	99	115	0.4626	1.134785e-03	**	REFUSE	0.024921	C > M
4	k300_84	456	246	210	0.5395	3.705847e-05	***	REFUSE	0.022031	C > M
5	k300_98	43	21	22	0.4884	6.530697e-01	-	ACCEPT	-0.013577	C ~ M
6	k300_108	53	28	25	0.5283	9.078006e-01	-	ACCEPT	0.001643	C ~ M
7	k300_121	77	38	39	0.4935	4.238187e-01	-	ACCEPT	0.011870	C ~ M
8	k300_140	706	350	356	0.4958	3.320716e-15	***	REFUSE	0.031823	C > M
9	k300_147	144	73	71	0.5069	9.841197e-03	**	REFUSE	0.027781	C > M
10	k300_191	347	187	160	0.5389	3.636025e-02	*	REFUSE	0.012703	C > M
11	k300_210	224	103	121	0.4598	1.037531e-02	*	REFUSE	0.021822	C > M
12	k300_222	459	217	242	0.4728	1.141437e-01	-	ACCEPT	0.009091	C ~ M
13	k300_293	102	49	53	0.4804	1.801141e-03	**	REFUSE	0.040428	C > M

Figure 12: Degree assortativity coefficient: Results representation for each topic considered

Proportion of topic by possible result:

- The topics with "C > M" are 7 / 14 (50.0 %)
- The topics with "C < M" are 1 / 14 (7.14 %)
- The topics with "C ∼ M" are 6 / 14 (42.86 %)

Topic result with the relative weighted frequency:

- "C > M" has a weighted frequency of 0.6525
- "C < M" has a weighted frequency of 0.0649
- "C ∼ M" has a weighted frequency of 0.2827

3.8.5 The Text Structure Analysis - Results discussion

For what concern the diameter and the average shortest path length (I put them together since I obtained the exactly same final result) even if there are only 4 topics with “C > M”, they contain more documents so we can say that there is a situation where the conspiracy documents tend to have a higher diameter and average shortest path length compared to the mainstream ones. This means that the text tends to have less connection between the words inside them and there is less efficiency in the information spread.
Moving to the clustering coefficient, the results show how the Mainstream Foma Mentis network tends to have a higher tendency to form knit clusters and this means that the words tend to be more cohesive with each other.
Finally the degree assortativity coefficient showed us how it tends to be bigger on the conspiracy side, with the implication that there is the general tendency to have words linked with the most similar ones.
So, summing up, this analysis points out that the conspiracy texts (taking into account the diversity of each Topic) tend to be less interconnected, with more dispersed but also with more redundant argumentation compared to the mainstream ones.

3.9 The Sentiment Analysis: How it has been performed the Z-score analysis

The focus of the next analysis is the comparison between the conspiracy and mainstream documents Z-score obtained for each emotion of the Plutchik's Wheel (Z-score analysis).

The principle applied and the procedure are the same used for the metrics computed on the Forma Mentis Networks.

So let's review again the steps followed for each topic:

1. The first step is to compute the Z-score associated with all the eight emotions of the Plutchik's wheel for all the documents.
2. Then I compute the Mann-Whitney U test for each of the two emotion distributions (one for the conspiracy and one for the mainstream) to verify if they come from the same population (null hypothesis).
3. If we accept the null hypothesis then I assign the "C $\sim$ M" in the Result column of the new table created.
4. If we reject the null hypothesis we check the output of the Hodges–Lehmann estimator:
   - If it is positive we assign "C $>$ M" in column Result;
   - If it is negative then the Result will be "C $<$ M".
5. Then, computing the weighted frequency, it is possible to draw conclusions at a high level.

The output table will have the same structure as the one computed above for the metrics:

- Topic_ID: it's the topic identification number from the k300 LDA output. As said before, these topics are filtered keeping only the only with a rate of conspiracy and mainstream that range between 0.45 and 0.55.
- N, N_C, N_M: these columns contain the number of documents inside the topic, the number of documents which are conspiracy and the number of mainstream ones.
- Prop_Conspiracy: is the proportion of conspiracy documents compared to the total number.
- pvalue: is populated with the p-value of the Mann-Whitney U test.
- *_sign_lev (where instead of the asterisk there is the name of the calculated index): is the significance level assigned to the test output on the base of the p-value:
  - "-" if it is higher than 0.05;
  - "*" if it ranges between 0.05 and 0.01;
  - "**" if it ranges between 0.01 and 0.001;
  - "***" if it is lower than 0.001.
- *_result (where instead of the asterisk there is the name of the calculated index): tell us if the null hypothesis is rejected ("REFUSE") or not ("ACCEPTED").

- HL_difference_estimate: it's the Hodges-Lehmann Estimate and becomes crucial in the case of rejection of the null hypothesis to understand which of the two sides tends to have a bigger value.
- Result: it tells us the final output of this analysis for that specific topic. It can assume these possible values:
  - "C $\sim$ M": we accepted the null hypothesis so we can say that there are no significant differences between the output of the Z-score computed for both sides;
  - "C $>$ M": we accepted the alternative hypothesis and the Hodges-Lehmann Estimate is positive so we can say that the Z-score computed for the conspiracy side tends to be higher compared to the mainstream one;
  - "C $<$ M": we accepted the alternative hypothesis and the Hodges-Lehmann Estimate is negative so we can say that the Z-score computed for the conspiracy side tends to lower compared to the mainstream one.

  For further details and a deep understanding of the reason behind the different choices made during this process, please refer to Chapter 3.8.

3.9.1 The Sentiment Analysis - The results obtained: Anger

The first emotion analysed is the anger (Figure 13).
Between the topics considered, it is quite evident that there are differences between the two categories. Out of the total 14 topics examined, the topics where the Z-score associated with the conspiracy side is higher than the mainstream ("C > M") constitute 6 out of 14 instances, accounting for 42.86% of the dataset.
Conversely, topics where the conspiracy Z-score value is lower than the mainstream one ("C < M") only make up 1 out of 14 instances, representing 7.14%.
Equally notable are the topics where conspiracy and mainstream show approximate parity ("C ∼ M"), comprising 7 out of 14 instances, accounting for exactly 50.0% of the dataset.
While these statistics provide a clear overview of the topic-level comparisons between the two alternative sides, a weighted frequency analysis offers deeper insights, considering the numerosity of each topic.
The weighted frequency for topics where the conspiracy Z-score is bigger than the mainstream ("C > M") is 0.6058, indicating a stronger prevalence of anger between the conspiracy documents.
In contrast, topics where conspiracy falls behind mainstream ("C < M") exhibit a weighted frequency of 0.1366, suggesting a lower impact of this situation within the dataset.
For topics where conspiracy and mainstream show approximate parity ("C ∼ M"), the weighted frequency is 0.2577, which means a moderate but noticeable presence in the dataset.

	Topic_ID	N	N_C	N_M	Prop_conspiracy	Anger_pvalue	Anger_sign_lev	Anger_result	Anger_HL_difference_estimate	Result
0	k300_3	89	42	47	0.4719	1.096992e-02	*	REFUSE	0.663536	C > M
1	k300_11	218	119	99	0.5459	6.506208e-01	-	ACCEPT	0.068263	C ~ M
2	k300_12	229	117	112	0.5109	2.455147e-01	-	ACCEPT	-0.195283	C ~ M
3	k300_37	214	99	115	0.4626	1.250973e-05	***	REFUSE	0.819054	C > M
4	k300_84	456	246	210	0.5395	1.232149e-02	*	REFUSE	0.231763	C > M
5	k300_98	43	21	22	0.4884	7.611117e-02	-	ACCEPT	0.519116	C ~ M
6	k300_108	53	28	25	0.5283	3.541542e-01	-	ACCEPT	0.299636	C ~ M
7	k300_121	77	38	39	0.4935	6.211848e-01	-	ACCEPT	0.179040	C ~ M
8	k300_140	706	350	356	0.4958	9.354936e-11	***	REFUSE	0.522571	C > M
9	k300_147	144	73	71	0.5069	9.204250e-01	-	ACCEPT	0.021160	C ~ M
10	k300_191	347	187	160	0.5389	1.344733e-05	***	REFUSE	0.595121	C > M
11	k300_210	224	103	121	0.4598	4.785233e-02	*	REFUSE	0.341909	C > M
12	k300_222	459	217	242	0.4728	1.506074e-02	*	REFUSE	-0.255180	C < M
13	k300_293	102	49	53	0.4804	7.051047e-01	-	ACCEPT	0.082773	C ~ M

Figure 13: Z-score analysis - Anger: Results representation for each topic considered

Proportion of topic by possible result:

- The topics with "C > M" are 6 / 14 (42.86 %)
- The topics with "C < M" are 1 / 14 (7.14 %)
- The topics with "C ∼ M" are 7 / 14 (50.0 %)

Topic result with the relative weighted frequency:

- "C > M" has a weighted frequency of 0.6058
- "C < M" has a weighted frequency of 0.1366
- "C ∼ M" has a weighted frequency of 0.2577

3.9.2 The Sentiment Analysis - The results obtained: Trust

The next emotion we are focusing on is trust (Figure 14).
Among our usual 14 topics selected, the topics where the Z-score related to the conspiracy viewpoint overtakes the one related to the mainstream ("C > M") constitute 5 out of 14, accounting for 35.71% of the dataset.
Conversely, there are no instances where the mainstream viewpoint has the higher value ("C < M"), making up 0% of the total.
The topics where the Conspiracy and Mainstream viewpoints are approximately equal ("C ∼ M") amount to 9 out of 14, representing 64.29% of the dataset.
However, when we move to the weighted frequency, which considers the numerosity of each topic, the weighted frequency of topics where the conspiracy viewpoint exceeds the mainstream viewpoint ("C > M") is 0.5213.
For topics where the mainstream Z-score falls behind one of the conspiracy viewpoints ("C < M"), the weighted frequency stands at 0.0, indicating a lack of presence of this particular scenario. The weighted frequency of topics where the conspiracy and mainstream viewpoints are comparable ("C ∼ M") is evaluated as 0.4787.
This suggests that, while a significant number of topics exhibit a similar level of trust between conspiracy and mainstream viewpoints, if we go deeper and focus on the document level those where the conspiracy trust level outweighs the mainstream viewpoint possess a slightly higher weighted frequency.
It is also notable that there are no topics where the Mainstream perspective overtakes the Conspiracy viewpoint according to the given dataset.

	Topic_ID	N	N_C	N_M	Prop_conspiracy	Trust_pvalue	Trust_sign_lev	Trust_result	Trust_HL_difference_estimate	Result
0	k300_3	89	42	47	0.4719	9.771085e-02	-	ACCEPT	-0.593067	C ~ M
1	k300_11	218	119	99	0.5459	9.209747e-01	-	ACCEPT	-0.014455	C ~ M
2	k300_12	229	117	112	0.5109	4.048655e-03	**	REFUSE	0.711666	C > M
3	k300_37	214	99	115	0.4626	3.571836e-02	*	REFUSE	0.548808	C > M
4	k300_84	456	246	210	0.5395	5.788753e-01	-	ACCEPT	-0.080065	C ~ M
5	k300_98	43	21	22	0.4884	7.521041e-01	-	ACCEPT	-0.233450	C ~ M
6	k300_108	53	28	25	0.5283	3.315043e-01	-	ACCEPT	-0.355984	C ~ M
7	k300_121	77	38	39	0.4935	4.980519e-01	-	ACCEPT	0.217401	C ~ M
8	k300_140	706	350	356	0.4958	9.907733e-22	***	REFUSE	1.212100	C > M
9	k300_147	144	73	71	0.5069	2.236381e-03	**	REFUSE	0.987687	C > M
10	k300_191	347	187	160	0.5389	3.044921e-01	-	ACCEPT	-0.182100	C ~ M
11	k300_210	224	103	121	0.4598	3.092722e-01	-	ACCEPT	-0.279972	C ~ M
12	k300_222	459	217	242	0.4728	5.359368e-14	***	REFUSE	1.299171	C > M
13	k300_293	102	49	53	0.4804	6.306622e-02	-	ACCEPT	0.552726	C ~ M

Figure 14: Z-score analysis - Trust: Results representation for each topic considered

Proportion of topic by possible result:

- The topics with "C > M" are 5 / 14 (35.71 %)
- The topics with "C < M" are 0 / 14 (0.0 %)
- The topics with "C ∼ M" are 9 / 14 (64.29 %)

Topic result with the relative weighted frequency:

- "C > M" has a weighted frequency of 0.5213
- "C < M" has a weighted frequency of 0.0 *
- "C ∼ M" has a weighted frequency of 0.4787

* In this case, the weighted frequency is 0 because there is no topic with that results prevalence. It follows that one number (number of documents inside the topics) multiplied by 0 (number of topics with that results prevalence) would be equal to 0.

3.9.3 The Sentiment Analysis - The results obtained: Surprise

With regard to the emotion surprise (Figure 15), out of the total 14 topics analysed, 3 of them (representing the 21.43% of the total) exhibit a higher tendency to have higher Z-score values between conspiracy theories with respect to the mainstream ones ("C > M"). On the contrary, a small portion of the 2 topics (14.29%) have bigger value in the mainstream narratives than in the conspiracy theories ("C < M").
The majority of the topics (9 topics out of 14, 64.29%) were observed to have similarities between both realms ("C ∼ M").
However, considering also the numerosity of the documents inside each argument, the topic classified as conspiracy which tends to have a greater Z-score than the mainstream ones ("C > M") has a weighted frequency of 0.3166. In contrast, those with higher values for the mainstream narratives ("C < M") have a weighted frequency of 0.2032. Lastly, the topics with similar values between conspiracy and mainstream ("C ∼ M") carried the highest weighted frequency (0.4802) and for this reason, we can not say that there is a strong difference between our two categories for the emotion surprise.

	Topic_ID	N	N_C	N_M	Prop_conspiracy	Surprise_pvalue	Surprise_sign_lev	Surprise_result	Surprise_HL_difference_estimate	Result
0	k300_3	89	42	47	0.4719	0.156271	-	ACCEPT	-0.341436	C ~ M
1	k300_11	218	119	99	0.5459	0.589027	-	ACCEPT	0.096488	C ~ M
2	k300_12	229	117	112	0.5109	0.481202	-	ACCEPT	0.101935	C ~ M
3	k300_37	214	99	115	0.4626	0.004039	**	REFUSE	0.485829	C > M
4	k300_84	456	246	210	0.5395	0.157323	-	ACCEPT	0.120209	C ~ M
5	k300_98	43	21	22	0.4884	0.826883	-	ACCEPT	0.059651	C ~ M
6	k300_108	53	28	25	0.5283	0.051037	-	ACCEPT	-0.560180	C ~ M
7	k300_121	77	38	39	0.4935	0.544350	-	ACCEPT	-0.240981	C ~ M
8	k300_140	706	350	356	0.4958	0.002251	**	REFUSE	0.221207	C > M
9	k300_147	144	73	71	0.5069	0.020360	*	REFUSE	0.499161	C > M
10	k300_191	347	187	160	0.5389	0.126064	-	ACCEPT	0.174051	C ~ M
11	k300_210	224	103	121	0.4598	0.010282	*	REFUSE	-0.374972	C < M
12	k300_222	459	217	242	0.4728	0.007525	**	REFUSE	-0.314373	C < M
13	k300_293	102	49	53	0.4804	0.975955	-	ACCEPT	-0.006801	C ~ M

Figure 15: Z-score analysis - Surprise: Results representation for each topic considered

Proportion of topic by possible result:

- The topics with "C > M" are 3 / 14 (21.43 %)
- The topics with "C < M" are 2 / 14 (14.29 %)
- The topics with "C ∼ M" are 9 / 14 (64.29 %)

Topic result with the relative weighted frequency:

- "C > M" has a weighted frequency of 0.3166
- "C < M" has a weighted frequency of 0.2032
- "C ∼ M" has a weighted frequency of 0.4802

3.9.4 The Sentiment Analysis - The results obtained: Disgust

The fourth Plutchik Emotion examined is the feeling of disgust (Figure 16).
At a topic level, among the 14 topics analysed, those were the conspiracy perspective registered higher values than the mainstream one ("C > M") accounting for 4 out of 14 topics (28.57%) while the situation where the mainstream has higher Z-score for disgust compared to the conspiracy ("C < M") amount to 3 out of 14 topics (21.43%).
The remaining 7 out of 14 topics (50%) present a situation where the conspiracy and mainstream documents have a value that comes from the same population ("C $\sim$ M").
However, when considering the weighted frequency, taking into account the numerosity of the topics, a different trend emerges.
The topics where the conspiracy Z-score exceeds the mainstream value ("C > M") have a weighted frequency of 0.3291 while topics where the mainstream Z-score tends to be higher compared to the conspiracy ones ("C < M") now have a weighted frequency of 0.3895.
The consequence is that now the weighted frequency computed for the topic where we accept the null hypothesis of the Mann-Whitney U test ("C $\sim$ M") is only 0.2815.
This difference is significant not only because it strongly changes the order of frequency of the three possible cases, but also because there is no longer a situation that clearly outperforms the others.

	Topic_ID	N	N_C	N_M	Prop_conspiracy	Disgust_pvalue	Disgust_sign_lev	Disgust_result	Disgust_HL_difference_estimate	Result
0	k300_3	89	42	47	0.4719	0.002490	**	REFUSE	0.800676	C > M
1	k300_11	218	119	99	0.5459	0.183301	-	ACCEPT	0.188721	C ~ M
2	k300_12	229	117	112	0.5109	0.764706	-	ACCEPT	0.049560	C ~ M
3	k300_37	214	99	115	0.4626	0.002214	**	REFUSE	0.469954	C > M
4	k300_84	456	246	210	0.5395	0.047560	*	REFUSE	0.209220	C > M
5	k300_98	43	21	22	0.4884	0.068409	-	ACCEPT	0.605032	C ~ M
6	k300_108	53	28	25	0.5283	0.073309	-	ACCEPT	0.371520	C ~ M
7	k300_121	77	38	39	0.4935	0.258062	-	ACCEPT	0.289107	C ~ M
8	k300_140	706	350	356	0.4958	0.001496	**	REFUSE	-0.258253	C < M
9	k300_147	144	73	71	0.5069	0.048839	*	REFUSE	-0.314603	C < M
10	k300_191	347	187	160	0.5389	0.004704	**	REFUSE	0.344253	C > M
11	k300_210	224	103	121	0.4598	0.060616	-	ACCEPT	0.290840	C ~ M
12	k300_222	459	217	242	0.4728	0.000007	***	REFUSE	-0.451596	C < M
13	k300_293	102	49	53	0.4804	0.371222	-	ACCEPT	-0.226272	C ~ M

Figure 16: Z-score analysis - Disgust: Results representation for each topic considered

Proportion of topic by possible result:

- The topics with "C > M" are 4 / 14 (28.57 %)
- The topics with "C < M" are 3 / 14 (21.43 %)
- The topics with "C $\sim$ M" are 7 / 14 (50.0 %)

Topic result with the relative weighted frequency:

- "C > M" has a weighted frequency of 0.3291
- "C < M" has a weighted frequency of 0.3895
- "C $\sim$ M" has a weighted frequency of 0.2815

3.9.5 The Sentiment Analysis - The results obtained: Joy

Another emotion that we have to keep in consideration is joy (Figure 17).
If we consider the count of topics as an indicator, we can see that 1 out of 14 topics (approximately 7.14%) register higher Z-score values on the conspiracy side compared to the ones of the mainstream perspective ("C > M"). On the other hand, 5 out of 14 topics (approximately 35.71%) tend to have greater values in the mainstream group than in the conspiracy ones ("C < M"). The majority of the arguments considered, 8 out of 14 topics (roughly 57.14%), tend to have similar scores for both the two categories ("C ∼ M").
These considerations strongly change if we take into account the number of documents inside each of the topics.
While before the most frequent category was the one where conspiracy and mainstream present similar Z-score ("C ∼ M") with a significant margin compared to the other two possible situations, now the conclusion has become not so obvious.
The weighted frequency of "C ∼ M" is 0.4859 while the one for the "C < M" is 0.4493.
The difference of only 0.0366 and none of the emotions registered a value of these metrics higher than 0.5. These considerations do not allow us to affirm without any doubt which is the prevalent situation between the documents analysed.
It is noteworthy that the possible case where a mainstream document tends to register a lower Z-score compared to the conspiracy ones ("C > M") almost disappears (weighted frequency of 0.0649).

	Topic_ID	N	N_C	N_M	Prop_conspiracy	Joy_pvalue	Joy_sign_lev	Joy_result	Joy_HL_difference_estimate	Result
0	k300_3	89	42	47	0.4719	0.000187	***	REFUSE	-1.297950	C < M
1	k300_11	218	119	99	0.5459	0.043639	*	REFUSE	0.513341	C > M
2	k300_12	229	117	112	0.5109	0.752556	-	ACCEPT	-0.042409	C ~ M
3	k300_37	214	99	115	0.4626	0.080261	-	ACCEPT	0.415274	C ~ M
4	k300_84	456	246	210	0.5395	0.976965	-	ACCEPT	0.002826	C ~ M
5	k300_98	43	21	22	0.4884	0.511805	-	ACCEPT	0.299820	C ~ M
6	k300_108	53	28	25	0.5283	0.387489	-	ACCEPT	-0.250475	C ~ M
7	k300_121	77	38	39	0.4935	0.338179	-	ACCEPT	-0.335019	C ~ M
8	k300_140	706	350	356	0.4958	0.000047	***	REFUSE	-0.331878	C < M
9	k300_147	144	73	71	0.5069	0.006121	**	REFUSE	-0.479993	C < M
10	k300_191	347	187	160	0.5389	0.023501	*	REFUSE	-0.292932	C < M
11	k300_210	224	103	121	0.4598	0.000120	***	REFUSE	-0.677117	C < M
12	k300_222	459	217	242	0.4728	0.338853	-	ACCEPT	-0.113561	C ~ M
13	k300_293	102	49	53	0.4804	0.132654	-	ACCEPT	-0.356211	C ~ M

Figure 17: Z-score analysis - Joy: Results representation for each topic considered

Proportion of topic by possible result:

- The topics with "C > M" are 1 / 14 (7.14 %)
- The topics with "C < M" are 5 / 14 (35.71 %)
- The topics with "C ∼ M" are 8 / 14 (57.14 %)

Topic result with the relative weighted frequency:

- "C > M" has a weighted frequency of 0.0649
- "C < M" has a weighted frequency of 0.4493
- "C ∼ M" has a weighted frequency of 0.4859

3.9.6 The Sentiment Analysis - The results obtained: Sadness

The next emotion analysed is sadness (Figure 18).
The first significant thing that we can notice is that there are no topics where the conspiracy Z-score registered a lower level compared to the mainstream one.
For what concerns the other two possible cases, what we have obtained is very similar to what we had above (even if before we were talking about the "C < M" category).
Looking at the number of topics, we have the situation where the conspiracy side registering similar value with the mainstream one is the most frequent (9 out of 14 topics with a 64.29 % of the total) compared to the case when the conspiracy has higher scores (5 topics over 14 with a 35.71 % of the total).
As anticipated the two possible circumstances registered much more similar values if we talk about the weighted frequency (respectively 0.5287 against 0.4713).

	Topic_ID	N	N_C	N_M	Prop_conspiracy	Sadness_pvalue	Sadness_sign_lev	Sadness_result	Sadness_HL_difference_estimate	Result
0	k300_3	89	42	47	0.4719	0.001491	**	REFUSE	0.790436	C > M
1	k300_11	218	119	99	0.5459	0.006623	**	REFUSE	0.490298	C > M
2	k300_12	229	117	112	0.5109	0.559457	-	ACCEPT	-0.097246	C ~ M
3	k300_37	214	99	115	0.4626	0.928547	-	ACCEPT	-0.013512	C ~ M
4	k300_84	456	246	210	0.5395	0.541439	-	ACCEPT	0.064086	C ~ M
5	k300_98	43	21	22	0.4884	0.131955	-	ACCEPT	0.525304	C ~ M
6	k300_108	53	28	25	0.5283	0.358811	-	ACCEPT	0.368578	C ~ M
7	k300_121	77	38	39	0.4935	0.617592	-	ACCEPT	0.123581	C ~ M
8	k300_140	706	350	356	0.4958	0.024606	*	REFUSE	0.183181	C > M
9	k300_147	144	73	71	0.5069	0.375023	-	ACCEPT	-0.173227	C ~ M
10	k300_191	347	187	160	0.5389	0.009644	**	REFUSE	0.306985	C > M
11	k300_210	224	103	121	0.4598	0.018877	*	REFUSE	0.383866	C > M
12	k300_222	459	217	242	0.4728	0.407780	-	ACCEPT	-0.082561	C ~ M
13	k300_293	102	49	53	0.4804	0.215303	-	ACCEPT	-0.307880	C ~ M

Figure 18: Z-score analysis - Sadness: Results representation for each topic considered

Proportion of topic by possible result:

- The topics with "C > M" are 5 / 14 (35.71 %)
- The topics with "C < M" are 0 / 14 (0.0 %)
- The topics with "C $\sim$ M" are 9 / 14 (64.29 %)

Topic result with the relative weighted frequency:

- "C > M" has a weighted frequency of 0.4713
- "C < M" has a weighted frequency of 0.0 *
- "C $\sim$ M" has a weighted frequency of 0.5287

* In this case, the weighted frequency is 0 because there is no topic with that results prevalence. It follows that one number (number of documents inside the topics) multiplied by 0 (number of topics with that results prevalence) would be equal to 0.

3.9.7 The Sentiment Analysis - The results obtained: Fear

For this emotion (Figure 19) there is again no topic with a higher value for the mainstream Z-score compared to the conspiracy.
For the other two possible cases the order does not change with the introduction of the number of documents for each topic as a variable but it increases the intensity of the delta.
The situation where the conspiracy side registered a higher Z-score is present in 8 over 14 topics (57.14%) with a weighted frequency of 0.6456.
On the other hand, the case when the two sides have similar values is present on 6 out of 14 topics (42.86%) with a weighted average of 0.3544.
It is pretty evident how the situation where the conspiracy texts tend to have a higher level of fear is predominant.

	Topic_ID	N	N_C	N_M	Prop_conspiracy	Fear_pvalue	Fear_sign_lev	Fear_result	Fear_HL_difference_estimate	Result
0	k300_3	89	42	47	0.4719	2.624363e-05	***	REFUSE	1.379120	C > M
1	k300_11	218	119	99	0.5459	3.428045e-02	*	REFUSE	0.388084	C > M
2	k300_12	229	117	112	0.5109	5.574439e-01	-	ACCEPT	-0.103556	C ~ M
3	k300_37	214	99	115	0.4626	6.483078e-01	-	ACCEPT	0.105116	C ~ M
4	k300_84	456	246	210	0.5395	1.424114e-03	**	REFUSE	0.346094	C > M
5	k300_98	43	21	22	0.4884	5.040198e-01	-	ACCEPT	0.198305	C ~ M
6	k300_108	53	28	25	0.5283	9.284543e-03	**	REFUSE	0.917836	C > M
7	k300_121	77	38	39	0.4935	3.908716e-02	*	REFUSE	0.607456	C > M
8	k300_140	706	350	356	0.4958	1.405687e-03	**	REFUSE	0.302509	C > M
9	k300_147	144	73	71	0.5069	4.417635e-01	-	ACCEPT	0.167098	C ~ M
10	k300_191	347	187	160	0.5389	1.856713e-08	***	REFUSE	0.869575	C > M
11	k300_210	224	103	121	0.4598	1.267316e-06	***	REFUSE	0.901172	C > M
12	k300_222	459	217	242	0.4728	5.035779e-01	-	ACCEPT	-0.078240	C ~ M
13	k300_293	102	49	53	0.4804	1.792927e-01	-	ACCEPT	0.338969	C ~ M

Figure 19: Z-score analysis - Fear: Results representation for each topic considered

Proportion of topic by possible result:

- The topics with "C > M" are 8 / 14 (57.14 %)
- The topics with "C < M" are 0 / 14 (0.0 %)
- The topics with "C ∼ M" are 6 / 14 (42.86 %)

Topic result with the relative weighted frequency:

- "C > M" has a weighted frequency of 0.6456
- "C < M" has a weighted frequency of 0.0 *
- "C ∼ M" has a weighted frequency of 0.3544

* In this case, the weighted frequency is 0 because there is no topic with that results prevalence. It follows that one number (number of documents inside the topics) multiplied by 0 (number of topics with that results prevalence) would be equal to 0.

3.9.8 The Sentiment Analysis - The results obtained: Anticipation

The last emotion faced is anticipation (Figure 20).
In both analyses, the relevant case is the one where conspiracy and mainstream tend to come from the same population and for this reason, have similar Z-score values (12 over 14 topics with an 85.71% of the total and a weighted frequency of 0.7233).
The other two possible situations cover only a marginal percentage portion: both are present in only one topic (7.14%) and have a low weighted frequency (0.2101 for "C > M" and 0.0666 for "C < M").

	Topic_ID	N	N_C	N_M	Prop_conspiracy	Anticipation_pvalue	Anticipation_sign_lev	Anticipation_result	Anticipation_HL_difference_estimate	Result
0	k300_3	89	42	47	0.4719	5.497692e-02	-	ACCEPT	-0.574417	C ~ M
1	k300_11	218	119	99	0.5459	3.661875e-01	-	ACCEPT	0.191323	C ~ M
2	k300_12	229	117	112	0.5109	7.858915e-02	-	ACCEPT	0.282521	C ~ M
3	k300_37	214	99	115	0.4626	9.050964e-02	-	ACCEPT	0.359175	C ~ M
4	k300_84	456	246	210	0.5395	9.213423e-01	-	ACCEPT	-0.010019	C ~ M
5	k300_98	43	21	22	0.4884	1.978119e-01	-	ACCEPT	-0.516456	C ~ M
6	k300_108	53	28	25	0.5283	7.416654e-01	-	ACCEPT	0.066354	C ~ M
7	k300_121	77	38	39	0.4935	2.623846e-01	-	ACCEPT	-0.360637	C ~ M
8	k300_140	706	350	356	0.4958	2.551704e-07	***	REFUSE	0.494043	C > M
9	k300_147	144	73	71	0.5069	4.405785e-01	-	ACCEPT	-0.180508	C ~ M
10	k300_191	347	187	160	0.5389	4.964460e-01	-	ACCEPT	0.100558	C ~ M
11	k300_210	224	103	121	0.4598	1.051668e-05	***	REFUSE	-0.805110	C < M
12	k300_222	459	217	242	0.4728	8.402471e-01	-	ACCEPT	-0.025649	C ~ M
13	k300_293	102	49	53	0.4804	1.575745e-01	-	ACCEPT	0.348073	C ~ M

Figure 20: Z-score analysis - Anticipation: Results representation for each topic considered

Proportion of topic by possible result:

- The topics with "C > M" are 1 / 14 (7.14 %)
- The topics with "C < M" are 1 / 14 (7.14 %)
- The topics with "C $\sim$ M" are 12 / 14 (85.71 %)

Topic result with the relative weighted frequency:

- "C > M" has a weighted frequency of 0.2101
- "C < M" has a weighted frequency of 0.0666
- "C $\sim$ M" has a weighted frequency of 0.7233

3.9.9 The Sentiment Analysis - Results discussion

Summing up the results, several emotions accept the null hypothesis of the Mann-Whitney U test: the two Forma Mentis texts (one for the conspiracy side and one for the mainstream) come from the same population and for this reason, present similar values.
Going into details, we have this situation:

- Surprise: the weighted frequency for the case where there is a similarity between the conspiracy and mainstream output has a value of 0.4802. Even if it is not above the threshold of 0.5, it has a relevant delta compared to the weighted frequency of the other possible situation ("C > M" has a value of 0.3166 and "C < M" of 0.2032);
- Sadness: it has a weighted frequency of 0.5287 for the case of acceptance of the Mann-Whitney U test null hypothesis but there is also a remarkable value for the situation where the conspiracy Z-score outperforms the mainstream one (0.4713);
- Anticipation: the weighted frequency is 0.7233 for the situation where we have a similar value between conspiracy and mainstream.

There are then two particular cases where it is not possible to determine with certainty which of the three possible situations is predominant.
I am talking about the emotions of:

- Joy: the peak of weighted frequency is touched by the case when conspiracy and mainstream have similar output (0.4859) but it is not enough because it neither exceeds the 0.5 threshold or to have a significant distance with the case in which the mainstream score is higher than the conspiracy score (0.4493). The delta is only 0.0366;
- Disgust: here the situation is even more complex. Neither one of the possible situations reaches 0.4 as weighted frequency. In detail, the case when the conspiracy Z-score exceeds the mainstream value has a value of 0.3291. The one where the mainstream Z-score tends to be higher compared to the conspiracy ones is 0.3895 and it is the peak for this emotion. Lastly, the case when we accept the null hypothesis of the Mann-Whitney U test is only 0.2815.

It is noteworthy that none of the emotions present a situation where the mainstream side has values that exceed the ones of the conspiracy.
Only joy presents high value for this case but, as seen above, it was not enough to be the predominant situation.

On the other hand, different emotions present a predominance of conspiracy Z-score compared to the mainstream side. In details:

- Anger: with a weighted frequency of 0.6058;
- Trust: here the peak has been touched by the situation where there are higher values for the conspiracy side with an amount of 0.5213 but there is also an important value for the weighted frequency of the case when conspiracy and mainstream have similar values (0.4787);
- Fear: where the weighted average arrived at 0.6456.

From our data, it appears that the emotions where there are discrepancies between the Z-score of the conspiracy text and the one of the mainstream side are anger, trust (even if

with a high level of “C $\sim$ M”) and fear.
All of these exhibit a situation where the conspiracy side tends to have values higher than the mainstream.
These are all emotions that can be associated with a reaction to an external impulse. In reality, as sustained by Robert Plutchik in his article “The Nature of Emotions” [11], this is not something that should surprise since ≪feelings do not happen in isolation. They are responses to significant situations in an individual’s life, and often they motivate action≫.
What is particular is the fact that if we create the three possible dyads (the combinations of two primary emotions) starting from the primary feelings we have found to be significant and we compare them with the possible output in Figure 5 we obtain:

- Submission (from trust and fear);
- Dominance (from trust and anger);
- Frozenness (from fear and anger).

These dyads represent the stereotype of the possible reaction to an external threat and dominance and this is not casual. Indeed, as reported by Jan-Willem van Prooijen and Karen M. Douglas in their article “Belief in conspiracy theories: Basic principles of an emerging research domain” [17], ≪people who are dispositionally likely to perceive their ingroup as superior or to perceive outgroups as threatening display increased belief in conspiracy theories.
Furthermore, experimental studies support the idea that the two key ingredients of intergroup conflict—a strong ingroup identity and a sense of outgroup threat—jointly stimulate belief in conspiracy theories. For instance, taking the perspective of members of a group increases belief in conspiracy theories, but only after receiving information that the group is under threat (Van Prooijen & Van Dijk, 2014). Likewise, self-uncertainty predicts increased conspiracy beliefs, but only among people who feel included in a group (Van Prooijen, 2016). These studies suggest that a strong ingroup identity increases conspiracy theories, but only in conjunction with a sense of threat. Experimental studies conducted in Indonesia yielded similar conclusions. People whose Muslim identity was made salient believed conspiracy theories, blaming terrorist attacks in Indonesia on a Western conspiracy more strongly than people whose Muslim identity was not made salient, but only when the West was described as threatening to Muslims (Mashuri & Zaduqisti, 2015).≫

3.10 Interpretation of results within the relevant literature

To strengthen the results obtained as well as to add credibility to them, I will compare the results obtained with the one of an article written by an expert in this subject.
The chosen article is “The Conspiratorial Mind: A Meta-Analytic Review of Motivational and Personological Correlates” [1] which identifies three main needs behind the tendency to be inclined to believe in conspiracy theories: ≪

- To form a reliable, certain, and stable view of the world (epistemic motives).
- To feel safe and in control, particularly in the face of threat (existential motives).
- To reinforce a superior, albeit fragile, image of oneself and one’s ingroup (social motives)≫ [1].

Are the results we have obtained in the previous chapters aligned with what the article argues?

Starting from the Existential motives, it is possible to notice how these motives are linked by a strong presence of an emotion: fear.
The fear of a threat and not being able to face it.
The fear of a world that is even more dangerous and unstable.
The fear of not being able to make changes in one’s environment.
This emotion is a constant, but this fact does not have to surprise us since it is aligned with what we obtained in our analysis. In Chapter 3.9.9 (and discussed in detail in 3.9.7) we have seen how fear is one of the three emotions with different Z-score distribution between conspiracy and mainstream and how the conspiracy one tends to have higher values for this emotion.

On the other hand, also the social motives match with what we obtained in our analysis. Indeed, in addition to the higher level of trust in the conspiracy texts, if we look at the dyads obtained we can see that from the combination of trust and anger we have dominance, which is exactly what the researchers highlighted above.

Unfortunately, we have not computed the necessary metrics to prove the epistemic motives and this is the reason why in the following chapters additional analysis will be performed to test also this motives.

Lastly, I want to stress one additional point. Between the causes mentioned by the article, there are ≪allied negative mood states, including anger and hostility≫. This is also perfectly aligned with what I have obtained in my analysis, since between the three emotions where the conspiracy text has higher Z-score levels compared to the ones of mainstream there is anger.

3.10.1 Additional analysis: specific analysis performed to check the presence of the Epistemic motives in the LOCO corpus

≪To summarize across all epistemic motives, conspiratorial ideation appears to be related to inflexible cognitive styles, including reliance on intuition, identifying patterns and agency in their absence, and maintaining one's views while being closeminded to alternative views. Still, individuals prone to conspiratorial ideation may also lack the cognitive abilities to evaluate information accurately and critically. . . ≫ [1]. These are the phrases used by the researchers to conclude the paragraph related to the Epistemic Motives and they represent what we are looking for.
The focus of the following additional research is to test if the text in the different topics contains a uniform view or if everyone bases their conviction on their instinct.
Using the same principle and procedure described above for the analysis of both the Forma Mentis Networks Metrics (Chapter 3.8) and the Z-score distribution of the emotion (Chapter 3.9) between conspiracy and mainstream documents, we are going to test if there are differences in the number of community detected and in the modularity index scores of the two sides.

Modularity is a measure that evaluates the strength of the division of a network into modules or communities. It assesses the extent to which a network can be divided into distinct groups or modules based on the connections between nodes.
It aims to identify communities or clusters in the network by maximising the number of within-module connections and minimising the number of between-module connections. High modularity suggests a network structure with dense connections within modules and sparse connections between modules.

To perform these two analyses on the number of communities detected and on the modularity, the first thing to do is choose the right community detection algorithm.
I have decided to go with two algorithms:

- Label Propagation Algorithm (LPA): it is a semi-supervised learning algorithm that assigns labels to unlabeled data points. It is based on the idea that similar data points are likely to have similar labels. The algorithm works by iteratively assigning labels to unlabeled data points based on the labels of their neighbours.
- Modularity Maximization Algorithm: It is a heuristic algorithm that aims to partition a network into a set of groups, such that the number of edges within groups is maximised relative to the number of edges expected by chance. The MMA starts with each node in its own community and iteratively merges pairs of communities that increase the modularity. This process continues until no further increase in modularity is possible.

The reasons why I choose these algorithms are:

- They are easy to implement;
- They are scalable (can be used with large datasets);
- They are effective and often able to find high-quality community structures in real-world networks.

Then, performing the usual process with the Mann-Whitney U test, we will be able to derive our conclusion.

3.10.2 Additional analysis - The results obtained: Number of community detected with the Label Propagation Algorithm (LPA)

Starting from the analysis of the number of communities detected by the Label Propagation Algorithm (Figure 21) we can see that the number of topics where the mainstream tends to have higher numerosity ("C < M") is zero. All the cases are distributed between the situation where the two sides have similar value ("C $\sim$ M": 6 topics over 14, 42.86% of the total) and the case where conspiracy has a higher value ("C > M": 8 topics over 14, 57.14% of the total).
If we move to the weighted frequency it is possible to notice how the principal situation became the one where conspiracy is the most frequent (0.7905) against the situation where they have similar values (0.2095). Obviously, the frequency for the case where the mainstream has the highest values is zero.

	Topic_ID	N	N_C	N_M	Prop_conspiracy	pvalue	LPA_sign_lev	LPA_result	HL_difference_estimate	Result
0	k300_3	89	42	47	0.4719	6.745850e-01	-	ACCEPT	-0.999957	C ~ M
1	k300_11	218	119	99	0.5459	4.434415e-01	-	ACCEPT	0.999996	C ~ M
2	k300_12	229	117	112	0.5109	4.252617e-03	**	REFUSE	2.999945	C > M
3	k300_37	214	99	115	0.4626	1.324302e-09	***	REFUSE	7.000063	C > M
4	k300_84	456	246	210	0.5395	1.307713e-11	***	REFUSE	4.000068	C > M
5	k300_98	43	21	22	0.4884	6.610261e-01	-	ACCEPT	-0.999960	C ~ M
6	k300_108	53	28	25	0.5283	4.526339e-01	-	ACCEPT	1.000022	C ~ M
7	k300_121	77	38	39	0.4935	1.840731e-01	-	ACCEPT	1.999915	C ~ M
8	k300_140	706	350	356	0.4958	3.493506e-30	***	REFUSE	4.999995	C > M
9	k300_147	144	73	71	0.5069	3.588107e-03	**	REFUSE	3.999951	C > M
10	k300_191	347	187	160	0.5389	5.482840e-04	***	REFUSE	2.999966	C > M
11	k300_210	224	103	121	0.4598	6.220481e-01	-	ACCEPT	0.000009	C ~ M
12	k300_222	459	217	242	0.4728	6.996132e-05	***	REFUSE	2.000012	C > M
13	k300_293	102	49	53	0.4804	3.494105e-03	**	REFUSE	4.999978	C > M

Figure 21: Number of topics detected - LPA: Results representation for each topic considered

Proportion of topic by possible result:

- The topics with "C > M" are 8 / 14 (57.14 %)
- The topics with "C < M" are 0 / 14 (0.0 %)
- The topics with "C $\sim$ M" are 6 / 14 (42.86 %)

Topic result with the relative weighted frequency:

- "C > M" has a weighted frequency of 0.7905
- "C < M" has a weighted frequency of 0.0 *
- "C $\sim$ M" has a weighted frequency of 0.2095

* In this case, the weighted frequency is 0 because there is no topic with that results prevalence. It follows that one number (number of documents inside the topics) multiplied by 0 (number of topics with that results prevalence) would be equal to 0.

3.10.3 Additional analysis - The results obtained: Modularity Index with the Label Propagation Algorithm (LPA)

Analysing the modularity produced by the Label Propagation Algorithm (Figure 22) we can see that looking at a topic level:

- The topic with "C > M" are 2 / 14 (14.29 %)
- The topic with "C < M" are 5 / 14 (35.71 %)
- The topic with "C ∼ M" are 7 / 14 (50.00 %)

While, if we take into account the numerosity of the topic with the weighted frequency, the results become:

- "C > M" has a weighted frequency of 0.1993
- "C < M" has a weighted frequency of 0.5225
- "C ∼ M" has a weighted frequency of 0.2782

As we can see the most frequent situation became the one where the mainstream Forma Mentis Network has a higher modularity.

	Topic_ID	N	N_C	N_M	Prop_conspiracy	pvalue	Modularity_LPA_sign_lev	Modularity_LPA_result	HL_difference_estimate	Result
0	k300_3	89	42	47	0.4719	0.156278	-	ACCEPT	0.050955	C ~ M
1	k300_11	218	119	99	0.5459	0.000352	***	REFUSE	-0.094639	C < M
2	k300_12	229	117	112	0.5109	0.003588	**	REFUSE	-0.070467	C < M
3	k300_37	214	99	115	0.4626	0.032090	*	REFUSE	0.051902	C > M
4	k300_84	456	246	210	0.5395	0.000352	***	REFUSE	0.059283	C > M
5	k300_98	43	21	22	0.4884	0.202109	-	ACCEPT	-0.056428	C ~ M
6	k300_108	53	28	25	0.5283	0.322728	-	ACCEPT	-0.036347	C ~ M
7	k300_121	77	38	39	0.4935	0.717577	-	ACCEPT	-0.016823	C ~ M
8	k300_140	706	350	356	0.4958	0.004214	**	REFUSE	-0.037576	C < M
9	k300_147	144	73	71	0.5069	0.034189	*	REFUSE	-0.049610	C < M
10	k300_191	347	187	160	0.5389	0.320957	-	ACCEPT	-0.017278	C ~ M
11	k300_210	224	103	121	0.4598	0.570842	-	ACCEPT	0.011165	C ~ M
12	k300_222	459	217	242	0.4728	0.000049	***	REFUSE	-0.060849	C < M
13	k300_293	102	49	53	0.4804	0.564604	-	ACCEPT	0.013894	C ~ M

Figure 22: Modularity - LPA: Results representation for each topic considered

Proportion of topic by possible result:

- The topics with "C > M" are 2 / 14 (14.29 %)
- The topics with "C < M" are 5 / 14 (35.71 %)
- The topics with "C ∼ M" are 7 / 14 (50.0 %)

Topic result with the relative weighted frequency:

- "C > M" has a weighted frequency of 0.1993
- "C < M" has a weighted frequency of 0.5225
- "C ∼ M" has a weighted frequency of 0.2782

3.10.4 Additional analysis - The results obtained: Number of community detected with the Modularity Maximization Algorithm (MMA)

Changing the Community Detection Algorithm the results do not change looking at a topic level (Figure 23): the situation where conspiracy tends to have a higher value ("C > M") is most frequent (8 topics over 14, 57.14% of the total) followed by the case when the two class have similar values ("C ∼ M": 6 over 14, 42.86% of the total) while no topic register the situation where the mainstream have the higher number of communities ("C < M").
Talking about the weighted frequency, there is a slight difference compared to the results obtained with Label Propagation Algorithm because the rank of the most frequent case remains equal but changes the weighted frequency score associated: the most frequent is "C > M" (0.8251), followed by "C ∼ M" (0.1749) and by "C < M" (0.00).

	Topic_ID	N	N_C	N_M	Prop_conspiracy	pvalue	MMA_sign_lev	MMA_result	HL_difference_estimate	Result
0	k300_3	89	42	47	0.4719	3.318136e-01	-	ACCEPT	-0.999904	C ~ M
1	k300_11	218	119	99	0.5459	4.162067e-04	***	REFUSE	1.000024	C > M
2	k300_12	229	117	112	0.5109	4.418859e-05	***	REFUSE	1.999949	C > M
3	k300_37	214	99	115	0.4626	5.534393e-06	***	REFUSE	1.999977	C > M
4	k300_84	456	246	210	0.5395	4.689303e-05	***	REFUSE	0.999964	C > M
5	k300_98	43	21	22	0.4884	8.546345e-01	-	ACCEPT	0.000028	C ~ M
6	k300_108	53	28	25	0.5283	6.929052e-01	-	ACCEPT	-0.000004	C ~ M
7	k300_121	77	38	39	0.4935	1.214405e-01	-	ACCEPT	0.999986	C ~ M
8	k300_140	706	350	356	0.4958	8.171448e-36	***	REFUSE	2.000037	C > M
9	k300_147	144	73	71	0.5069	1.854421e-03	**	REFUSE	1.999990	C > M
10	k300_191	347	187	160	0.5389	1.581678e-02	*	REFUSE	0.999957	C > M
11	k300_210	224	103	121	0.4598	2.455499e-01	-	ACCEPT	-0.000030	C ~ M
12	k300_222	459	217	242	0.4728	6.180343e-10	***	REFUSE	1.999967	C > M
13	k300_293	102	49	53	0.4804	9.583826e-02	-	ACCEPT	1.000076	C ~ M

Figure 23: Number of topics detected - MMA: Results representation for each topic considered

Proportion of topic by possible result:

- The topics with "C > M" are 8 / 14 (57.14 %)
- The topics with "C < M" are 0 / 14 (0.0 %)
- The topics with "C ∼ M" are 6 / 14 (42.86 %)

Topic result with the relative weighted frequency:

- "C > M" has a weighted frequency of 0.8251
- "C < M" has a weighted frequency of 0.0 *
- "C ∼ M" has a weighted frequency of 0.1749

* In this case, the weighted frequency is 0 because there is no topic with that results prevalence. It follows that one number (number of documents inside the topics) multiplied by 0 (number of topics with that results prevalence) would be equal to 0.

3.10.5 Additional analysis - The results obtained: Modularity Index with the Modularity Maximization Algorithm (MMA)

Lastly, the score for the Modularity is computed with the Modularity Maximization Algorithm (Figure 24).
Looking at a topic level we can see how:

- The topic with "C > M" are 2 / 14 (14.29 %)
- The topic with "C < M" are 4 / 14 (28.57 %)
- The topic with "C ∼ M" are 8 / 14 (57.14 %)

If we take into account the numerosity of the topic with a weighted frequency, the results become:

- "C > M" has a weighted frequency of 0.1993
- "C < M" has a weighted frequency of 0.3124
- "C ∼ M" has a weighted frequency of 0.4882

As we can see the modularity gives us different results compared to the one obtained with the Label Propagation Algorithm. Here the most frequent situation is the one where conspiracy and mainstream have similar scores, while above it is "C < M".
It is important to highlight that the situation "C ∼ M" does not exceed the 0.5 benchmark and that in any case "C < M" registered also with the MMA a significant value.

	Topic_ID	N	N_C	N_M	Prop_conspiracy	pvalue	Modularity_MMA_sign_lev	Modularity_MMA_result	HL_difference_estimate	Result
0	k300_3	89	42	47	0.4719	3.220096e-01	-	ACCEPT	0.017623	C ~ M
1	k300_11	218	119	99	0.5459	4.392214e-04	***	REFUSE	-0.045693	C < M
2	k300_12	229	117	112	0.5109	2.629477e-03	**	REFUSE	-0.036162	C < M
3	k300_37	214	99	115	0.4626	4.757254e-03	**	REFUSE	0.029730	C > M
4	k300_84	456	246	210	0.5395	1.298459e-05	***	REFUSE	0.032968	C > M
5	k300_98	43	21	22	0.4884	6.014098e-01	-	ACCEPT	-0.013577	C ~ M
6	k300_108	53	28	25	0.5283	2.026828e-01	-	ACCEPT	-0.025747	C ~ M
7	k300_121	77	38	39	0.4935	7.559864e-01	-	ACCEPT	-0.005853	C ~ M
8	k300_140	706	350	356	0.4958	6.585075e-01	-	ACCEPT	-0.002611	C ~ M
9	k300_147	144	73	71	0.5069	3.913526e-03	**	REFUSE	-0.047193	C < M
10	k300_191	347	187	160	0.5389	3.467243e-01	-	ACCEPT	-0.007380	C ~ M
11	k300_210	224	103	121	0.4598	8.555500e-01	-	ACCEPT	0.002538	C ~ M
12	k300_222	459	217	242	0.4728	8.236564e-08	***	REFUSE	-0.042008	C < M
13	k300_293	102	49	53	0.4804	7.326588e-01	-	ACCEPT	-0.005014	C ~ M

Figure 24: Modularity - MMA: Results representation for each topic considered

Proportion of topic by possible result:

- The topics with "C > M" are 2 / 14 (14.29 %)
- The topics with "C < M" are 4 / 14 (28.57 %)
- The topics with "C ∼ M" are 8 / 14 (57.14 %)

Topic result with the relative weighted frequency:

- "C > M" has a weighted frequency of 0.1993
- "C < M" has a weighted frequency of 0.3124
- "C ∼ M" has a weighted frequency of 0.4882

3.10.6 Additional analysis - Results discussion

Summing up our results, using both the algorithms we have obtained, the conspiracy documents tend to have a higher number of communities detected.
On the other hand, the considerations regarding the modularity score are not so obvious. Both the Label Propagation Algorithm and the Modularity Maximization Algorithm have registered a significant weighted frequency for the "C < M" option but, while in the LPA it was the most frequent one (0.5225), in the MMA ("C < M": 0.3124) the most spread case is the one where the two sides have similar values (0.4882).
Even if "C < M" is not the prevalent case between the MMA Modularity results, it registers a significant value and "C $\sim$ M" does not reach the 0.5 level. For this reason, I decided to keep as a benchmark the result obtained in the LPA and so to consider modularity as a metric that tends to have higher value on the mainstream side.

Do these results make sense?
What appears from our analysis is that the conspiracy texts tend to:

- Be more heterogeneous compared to the mainstream ones (there tend to be more communities);
- Have a lower clear division between communities (argumentation) compared to the mainstream ones (lower modularity).

These considerations are aligned with what the researchers write in the article "The Conspiratorial Mind: A Meta-Analytic Review of Motivational and Personological Correlates" [1]. Indeed they underline how conspiracists tend to rely more on self-intuition creating links between arguments that potentially have nothing to do with each other. This implies a strong diversity between communities and also lower well-defined boundaries between one argumentation and another.

After this additional research, it is possible to conclude that also in the LOCO dataset there is evidence of a less flexible cognitive style among conspiracist people, who tend to strongly rely on intuition and not on a critical assessment of facts.

4 Conclusions

The aim of this research was to analyse the LOCO dataset with a new approach based on the Textual Forma Mentis Network in order to investigate the conspiracy text and see if there are differences compared to the Mainstream one.
The analysis focused on two main aspects:

- The text structure: it has been analysed with several metrics computed on the Forma Mentis Network obtained by each document accounted and for each topic considered.
- The emotions characterising the document inside the topics considered (the Plutchik's wheel of emotions is the reference)

To do it, I follow four main steps.
At the beginning, I find what the literature says about this subject (Chapter 2). I read several articles and what came out is that the conspiracist world is even more complex than what is commonly believed. Conspiracy believers are not necessarily mentally ill, on the contrary, it has been proved that there are several reasons that can make a person inclined to believe in this type of argumentation. From the own of specific personality traits (such as dogmatism, low cognitive ability or the need for certainties) to motivational factors (for instance the constant perception of danger or threat, the tendency to rely on intuition or to act as a superior person) passing through the people with a specific background of experiences.
Understanding this complexity is crucial if one wants to analyse and understand this way of seeing the world and prevent its expansion.

The following step consists of performing several metrics on the Textual Forma Mentis Networks obtained from the documents inside the topic considered and then comparing the results using the Mann-Whitney U Test (Chapter 3.8). In particular, it has been computed the diameter, the average shortest path length, the clustering coefficient and the assortativity coefficient.
Before this computation, the topics have been filtered keeping only the ones discussed from both the conspiracy and mainstream side (the proportion between the two must range range between 0.45 and 0.55) and considering only the LDA topic classification with 300 topics. The results show how the conspiracy texts (taking into account the diversity of each Topic) tend to be less interconnected, with more dispersed but also with more redundant argumentation compared to the mainstream ones.
This is the first sign that makes us understand that there is a different way of writing (and also to think) between the two sides. In particular, the results seem to confirm the consideration made above on the tendency of conspiracists to rely on intuition, putting together arguments completely different from each other and using them in a redundant way to create a sort of base to which everything can be related.

The third step is the emotional analysis (Chapter 3.9).
The reference is the Plutchik's wheel, that divides the possible sentiments into eight primary emotions, which are the basis for all the others, and that can be grouped into four opposites polar:

- joy and sadness
- trust and disgust

- fear and anger
- surprise and anticipation

Thanks to the EmoAtlas library it is possible to obtain the Z-score relative to each one of these emotions and then the procedure applied is the same used for the Forma Mentis Networks metrics.
The analysis shows us that there are three emotions that tend to have difference statistically significant between conspiracy and mainstream text. They are anger, fear and trust, where in all three cases there is a higher value for the conspiracy side.
Noteworthy is the fact that the dyads (the combinations of two primary emotions) that can be obtained are:

- Submission (from trust and fear)
- Dominance (from trust and anger)
- Frozenness (from fear and anger)

All of these three dyads represent the stereotype of the possible reaction to an external threat and dominance, matching with what the theories say: the conspiracy belief tends to spread easily in individuals with fear or who tend to act as superior. Indeed, as reported by Jan-Willem van Prooijen and Karen M. Douglas in their article "Belief in conspiracy theories: Basic principles of an emerging research domain" [17] ≪people who are dispositionally likely to perceive their ingroup as superior or to perceive outgroups as threatening display increased belief in conspiracy theories≫.

Lastly, I have compared my results with what is known by the literature (Chapter 3.10).
I have done it to make my results stronger and add credibility to them.
The article chosen is "The Conspiratorial Mind: A Meta-Analytic Review of Motivational and Personological Correlates" [1], because it was one of the first meta-analyses to challenge the traditional view of conspiracy as a symptom of mental illness.
The main news introduced by this article is that there are three main motivational needs which (in the absence of them) make individuals more likely to become conspiracists:

- A world that is stable and reliable (Epistemic motives)
- To feel safe and in control of possible threats (Existential motives)
- To feel better / superior compared to other members of a group (Social motives)

For what concern the Existential and the Social motives, our results confirm their presence in the LOCO corpus since the conspiracy side present higher level of fear and the dominance dyads.
Regarding the Epistemic motives, further analyses have been required.
In particular, four additional metrics have been computed on the Forma Mentis Networks. For both the label propagation algorithm (LPA) and the modularity maximization algorithm (MMA) it has been computed the number of communities detected and the modularity index. Then the same procedure was performed as for the other analyses.
The output shows how the conspiracy text tends to be more heterogeneous compared to the mainstream ones (more communities on the conspiracy side) and to have a lower clear division between communities (argumentation) compared to the mainstream ones (lower

modularity in the conspiracy side).
This implies that also the presence of Epistemic motives is confirmed by our data.

As we have seen, to truly understand the conspiracy worldview and limit its spread with all the relative negative consequences, which can reach violence and extremism, there is a need to acknowledge the complexity of the picture. A multitude of reasons can explain why people can start to believe in conspiracy theories and it is not easy to prevent all of them.
Probably the main strength of the conspiracy views is their ability to provide easy and understandable explanations to everyday problems, which contrast with the complex and not-so-easily accessible version of the public authorities or researchers. This characteristic makes these theories interesting in a world where everything is faster than ever and there is even less time to spend verifying the information we receive.
Indeed, as Anne Applebaum has written in her book "Twilight of democracy: the seductive lure of authoritarianism" [18], ≪the emotional appeal of a conspiracy theory is in its simplicity. It explains away complex phenomena, accounts for chance and accidents, offers the believer the satisfying sense of having special, privileged access to the truth.≫

On the other hand, as shown in this research, using new approaches and technologies (like the one based on the Forma Mentis Networks and on the EmoAtlas library) it is possible to better identify the patterns which differentiate the conspiracy texts from the others. By focusing on them, it is possible to obtain a clearer picture of what makes these theories so attractive, being able to act faster and more effectively to limit their spread.

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