Disentangling the Climate Divide with Emotional Patterns: a Network-Based Mindset Reconstruction Approach

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Abstract:

Extreme political populism has been fiercely spreading climate disinformation for years, contributing to a social divide about climate change. In order to profile how both sides of the climate divide communicate climate change, we collected dissemination materials and analysed the mindset of key actors reaching global audiences. We apply network science to textual content, to reconstruct and analyse the mindset of key actors across the climate divide. Here we show that the emerging mindset supports the identification of emotional patterns linked to a quick and pervasive spread of falsehoods — i.e. an infodemic — such as hypercritical scepticism masking falsehoods, under a trustful promotion of change. We find that the word "climate" represents a fearsome threat linked to inconsistent science in climate change disinformation. We show that the word "change" represents a reassuring pattern in climate disinformation, characterized by trust and by low anticipation without risk awareness, except for some fear about policy changes. For climate activism the word "change" is linked to high levels of negative emotions like anger, disgust and fear, related to a perception of existential threats. Furthermore, the word "children" represents an angering concern in climate disinformation, while climate change activism perceives "children" with trust and joy, but sadness for their anticipated future. Mindset reconstruction has the potential to become a relevant tool to identify and flag communication materials linked to disinformation, that amplify the climate divide and facilitate infodemics.

Keywords:

Fridays for future, social movements, infodemics, climate emergency, revolution.

Main text:

1. Introduction.

The Intergovernmental Panel on Climate Change (IPCC) affirms that continued climate change is directly impacting human lives, and that risks of injury, disease, and death increase with heat waves, floods, droughts, and fires (Smith et al., 2014). However, contrasting messages from extreme political populism have been fiercely spreading climate disinformation through social and news media for years (Demelle, 2016; Horton, 2020; Watts et al., 2019).

Climate denying political leaders across world regions —USA, Brazil, Australia, the Netherlands — are just visible elements of an evolving list of hundreds of influential players and think tanks (Desmog, 2021). These think tanks repeatedly appear linked to events where influencers take climate denying positions (Youtube, 2019), often these events run in parallel to the Conferences of Parties (COPs) of the United Nations Climate Change Framework Convention (UNFCCC). These annual COPs are the most important climate policy event worldwide. When searching information about these UNFCCC COP events, content intended to trigger a quick and pervasive spread of falsehoods — i.e. an infodemic — from events organized in parallel by climate disinformation think tanks shows up in multiple media channels, including in prominent video-sharing platforms (see Methods section).

These actors and think tanks have been polarizing the worldwide public opinion for decades, amplifying the climate divide (Hoffman, 2011, Horton 2020). On one side of the climate divide, climate change disinformation actively impedes "social consensus" about climate change. Climate change disinformation actors (hereafter *climate disinformation*) disseminate misleading information and downplay scientific evidence with the support of politically entrenched think tanks (Demelle, 2016; Desmog, 2021; Horton, 2020).

On the other side of the climate divide, science-based climate change activism (hereafter *climate activism*) demand action from policy makers while stressing the importance of climate science in society (Hoffman, 2011; Marris, 2019). While environmental and climate activists are not a novelty, and while cohorts of teenagers and students have been involved in the decarbonization of UK and US universities at least since 2010 (Healy & Debski, 2017), recently the *#FridaysForFuture* movement gained unprecedented prominence demanding climate action from political leaders. The *#FridaysForFuture* movement adheres to scientific consensus on climate change and gathered remarkable media attention since 2019.

Social movements like #FridaysForFuture have been pointed out as instrumental for crossing a tipping point toward major changes of social norms and values that could contribute to stabilize Earth's climate (Otto et al., 2020). Information flows and the feedbacks they might activate are amongst the most important interventions to stabilize Earth's climate (Otto et al., 2020). The fear of information flows and their related feedbacks activating social tipping dynamics towards decarbonization by certain think tanks provide a possible explanation for their interest on a climate emergency infodemic and polarization agenda.

The variety of actors involved in the climate divide is immense, and it is fully unclear what underlying patterns could characterize the messages in both sides of this divide. In this context, we structure our investigation as a comparison between key representatives in their ranks, i.e. individuals with outstanding character that managed to exhibit leadership in a history of world-spanning events reaching millions of individuals.

To elaborate overarching strategies and understand the validity of proposals for tools dealing with the climate divide, it is fundamental to explore the emotions inflaming this battle of ideas, and to uncover weaknesses in the mindset embedded in the communication strategy of those involved (Hoffman, 2011). The communication materials of individuals involved in the climate divide can be expected to hold patterns leading to the identification of inflammatory media content. Semantic patterns can be used to unveil emotionally distorted content linked to polarization (Stella et al. 2018, Stella 2020).

In this article, we aim to explore the emotional dimension of climate communication linked to the climate divide. Departing from this aim, we have specified the following objectives: First, to explore how the mindset of key representatives of *#FridaysForFuture* and of climate-denying think tanks differ when communicating about climate. Second, to unveil emotionally distorted content linked to polarisation in key climate disinformation communication events. And third, to provide a scientific basis for unveiling disinformation content driving a climate emergency infodemic.

2. Methods.

The conceptual and methodological innovations in this article have an exploratory character. Mindset reconstruction exposes the emotional backbone of language, i.e. how words eliciting different emotions are syntactically and semantically linked in language (Stella, 2020; Stella et al., 2018). In order to profile how both sides of the divide communicate “climate change”, we collected communication materials related to climate change and analysed the mindset of selected actors who have been able to reach global audiences. The methodology is divided in three consecutive steps: (i) identification of global key influencing figures of the climate divide, (ii) data collection, (iii) application of network science methods for mindset reconstruction and visual representation of the results. The proposed methodology contributes to formalise data-driven approaches in the human dimension of global change, in particular about social and opinion dynamics of the climate divide.

2.1. Identification of key figures.

The identification of key figures is based on criteria of leadership and of a history of contribution to global events in the respective networks of *#FridaysForFuture* and of climate denying think tanks. This has been a difficult task, because while there are prominent figures in both sides of the climate divide, very few have a truly remarkable history of contribution to international events. Demelle (2016) and Desmog (2021) have been instrumental sources to evaluate climate deniers.

Greta Thunberg can be traced as the originator of the *#FridaysForFuture*. After her innovative way of demonstrating gained prominence, her initially single-student protest gained scale and lead to a global school strike movement. Afterwards, she gave speeches in many global centres of power and meet with multiple global leaders. At the moment of writing this article she is perhaps the only globally mediatic figure of this movement.

Christopher Monckton was ranked a top ten climate denier by Demelle (2016), and Desmog (2021) mentions him in the context of multiple climate-related events and actions spanning across world regions for more than a decade.

2.2. Data collection.

Data originates from key public speeches directly or incidentally linked to international bodies, national institutions, and diplomacy hubs. For example, a COP of the UNFCCC, the UN, the World Economic Forum at Davos, the UK parliament, or climate disinformation conferences.

The selected key public speeches reached broad audiences beyond the auditorium and have been disseminated by multiple media channels, including television, newspapers, and video-sharing platforms like Youtube (Youtube, 2019). In particular, we selected 11 public speeches by Greta Thunberg from 2018 to 2020, and three much larger speeches in 2019 by Christopher Monckton in events organised in Madrid in parallel to UNFCCC's COP 25, and in a climate disinformation conference in Washington. Thunberg's speeches included a total of 600 sentences and 9168 words, whereas Monckton's speeches included a total of 568 sentence and 15178 words. The word counts in here consider also repetitions and not include lemmatization, which is rather performed within the construction of *forma mentis* networks.

By using text from public speeches, we overcome the difficulties of preserving the privacy of under-age citizens that are a known part of the *#FridaysForFuture* movement (Marris, 2019).

2.3. From words to mindset reconstruction with *forma mentis* networks.

The mental lexicon is an idealised system that acquires, stores, processes and produces language (Vitevitch, 2019). The mental lexicon represents the structure of conceptual associations in language as used by each individual. As a purely cognitive system, the mental structure of conceptual associations in the lexicon can be extracted and analysed from communication materials under the assumption of the individual's authorship.
Communication materials like texts are an open view of the mindset of the authors, which is a proxy for the structure of language and its associations in the human mind. For instance, Teixeira and colleagues (2021) reconstructed associations in suicide letters to assess how

suicide ideation altered perceptions of concepts like “life” and “love” in comparison to healthy individuals.

Forma mentis networks are a representation of the emotional content of the mental lexicon and the relations between the meanings involved (Stella, 2020). We use *forma mentis* networks to show how an individual person conceptually and emotionally structure their mindset about climate change. Mindset reconstruction with *forma mentis* networks exposes the emotional backbone of language, and such exposure highlights the attitudes towards “climate change” fuelling the climate divide (Figure 1, Text Box 1).

To build the *forma mentis* networks, syntactic networks are used as a proxy of the mental lexicon. Relations between words come from syntactic and semantic dependencies in speeches and written text. Syntactic dependencies specify features or meanings of words. For instance, in “the pen is on the table”, the syntactic relationship “pen” – “table” specifies the location of the word “pen”. In textual *forma mentis* networks (TFMNs), as implemented here and in (Stella 2020), syntactic links between words are detected through artificial intelligence (AI) rather than by human intervention. In this work, the AI performing syntactic parsing is a multilayer perceptron, i.e. a neural network architecture where different layers of nodes perform computations iteratively and can learn to predict specific output based on extensive input. Chen and Manning (2014) trained a multilayer perceptron with 3 layers to identify syntactic relationships in English on a dataset with 39,000 sentences. The AI achieved an accuracy of 92% in correctly assessing whether two words were syntactically linked or not. In a single sentence, once retrieved, syntactic links create a tree graph T, where words are nodes and links indicate syntactic dependencies, e.g. in “the pen is on the table”, “on” depends on “the” and they are thus linked. Considering directly these trees would be problematic since grammatical rules for stopwords (i.e. prepositions and articles) would automatically make the latter largely connected nodes, e.g. “the” will appear more frequently in sentences and thus get more connections. To address this issue, we build new syntactic links between all pairs of non-stopwords on T if separated by at most K=4 syntactic dependencies. This approach leads to networks of non-stopwords clustered by local syntactic dependencies. To reduce language variability, we also lemmatize words with WordNet (Miller 1995), e.g. “pens” and “pen” in the text are represented by a single “pen” node. We enrich TFMNs semantically by considering semantic relationships indicating overlap in meaning, i.e. synonyms as extracted from WordNet 3.0 (Miller 1995). Nodes/words in TFMNs can thus be connected syntactically and semantically. Words are also attributed psycholinguistic labels expressing valence/pleasantness. A single word can be identified as “positive”, “negative” or “neutral” as indicated by human raters involved in a psychological mega-study (cf. Stella 2020). Links are treated as undirected and unweighted. Only for visualisation purposes, links between any two neutral words appearing more than once are highlighted in thicker grey lines. Links involving one positive (negative) word are highlighted in cyan (red). Links between one positive and one negative words are highlighted in purple. Green links indicate synonyms.

Notice that syntactic parsing is different from considering word co-occurrences. In the example “climate change is a terrible, catastrophic, problematic, crucial issue”, the words “change” and “issue” are evidently syntactically related but they are neither adjacent nor close in the layout of the sentence. Syntactic parsing and our TFMNs would thus link these words, unlike a word co-occurrence network of adjacent words (i.e. where links would be between “climate” and “change”, “change” and “is”, “is” and “a”, etc.).

TFMNs represent syntactic/semantic networks of words labelled on an affective level. These networks encode the structure of associative knowledge, expressed through semantic and syntactic word associations in one or more texts. Stella (2020) showed that in labelled data, this network construction successfully identifies keywords in tagged texts. Investigating the structure of TFMNs can thus be informative about ways of associating ideas and structuring emotional stances. Here we investigated TFMNs by focusing on network neighbourhoods, which are interpreted as semantic frames providing contextual information, i.e. the set of words that were syntactically/semantically associated to a target word to specify the meaning of the latter. In "the pen is on the table", the neighbourhood of "pen" would be "table", specifying the location of the "pen" itself. According to frame semantics in cognitive science (Fillmore & Baker, 2001), the meaning attributed to a target word in a text can be reconstructed by considering its syntactic, semantic and emotional associations. Focusing on direct associations, i.e. at distance one from a given target, network neighbourhoods encode contextual knowledge that indicates how the same concept (e.g. represented by the word "failure") can be framed in different ways within various narratives (e.g. "failure is a disappointing experience" vs. "failure is a learning opportunity"). TFMNs automatise the identification of semantic frames in texts as network neighbourhoods or, in other words, as ego-centered networks of radius 1 (Newman 2003), surrounding a target word/idea. Reconstructing these neighbourhoods enables a quantitative understanding of how concepts were framed in texts. This approach has been used to texts of varying sizes, including to suicide notes of about 120 words (Teixeira et al., 2021), where "love" was found to be framed with considerably sadder jargon compared to reference associations to "love" provided by mentally healthy individuals.

Emotions populating a given semantic frame are computed through the NRC Emotion Lexicon (Mohammad & Turney, 2013), which is a large-scale lexicon mapping 14,000 English words to 8 emotional states, like fear, anger, joy, anticipation, sadness, trust and surprise and disgust, which go far beyond simple positive/negative sentiment polarities..

Emotional profiling is performed through counting operations. In a given semantic frame/neighbourhood, let *L* be the list of words eliciting at least one emotion according to the NRC Emotion Lexicon. The emotional richness *r(e)* is then defined as the number of words in *L,* which elicit emotion *e,* normalised by the neighbourhood size. Emotional richness *r(e)* thus defines the probability of finding one word eliciting a given emotion by sampling uniformly at random one word in a specific semantic frame, surrounding a target idea/concept.

Notice that network construction and visualisation were both performed within Mathematica 11.3. Network construction adopted the commands TextStructure[] (syntactic parsing) and WordData[] (lemmatization, deletion of articles and prepositions), see for reference: https://www.wolfram.com/language/11/text-and-language-processing/explore-the-structure-of-texts.html?product=language (Last Accessed: 19/07/2022). Network visualisation adopted a hierarchical edge bundling clustering, placing nodes on a circular embedding while grouping clusters of links together, (cf. Holten 2006).

The words in the *forma mentis* networks also identify their key concepts in the analysed speeches with the size of the words (see Figure 1), larger words were represented as possessing a higher closeness centrality in the speeches (see Formula 1). Closeness centrality is defined as the inverse average distance between a word and all its neighbours in the full network (Metcalf & Casey, 2016). A previous study (Stella, 2020) showed that closeness centrality is able to identify prominent concepts of short texts, i.e. the main words providing grounding to a short narrative. This motivates our choice to use closeness centrality as an estimator for concept prominence in texts. Eq. (1) is used for calculating the closeness centrality (Metcalf & Casey, 2016) of each concept:

(1)

Where: $$C(v) = \sum_{w \in G} \frac{N-1}{d(v,w)}$$

C is the closeness centrality for each node in the graph G, in this case a network made of words from speeches and written text, where links indicate syntactic (e.g. “pen” – “table” in the sentence “the pen is on the table”) and synonym relationships (e.g. “nice” and “good” overlap in meaning in the sentence “you are nice and good”).

G is the whole network, which includes words (nodes) and semantic and syntactic links as extracted from all sentences in a speech/text.

v is the node in network G, which in our case is a word in a speech or written text; the closeness centrality is computed for this *v* node.

w represents any other node in network G.

N is the number of nodes in network G.

d is the shortest path network distance, i.e. the smallest number of links between nodes (words) *v* and *w* in the graph G.

3. Results.

As detailed in the Methodology above, mindset reconstruction exposes the emotional backbone of language (Stella et al. 2018, Stella 2020). Such exposure importantly allows to highlight the attitudes towards “climate change” that fuel the climate divide. In order to profile how both sides of the divide perceive “climate change”, we illustrate their emotional and semantic patterns in Figures 1-4 and Text Box 1, accompanied in Appendix A by Figures A1-A12. Overall, here we show that speeches in climate activism rely mostly of trust and hope with links to anger, while climate disinformation shows clear patterns of hypercritical misinformation masked under trust-inspiring content.

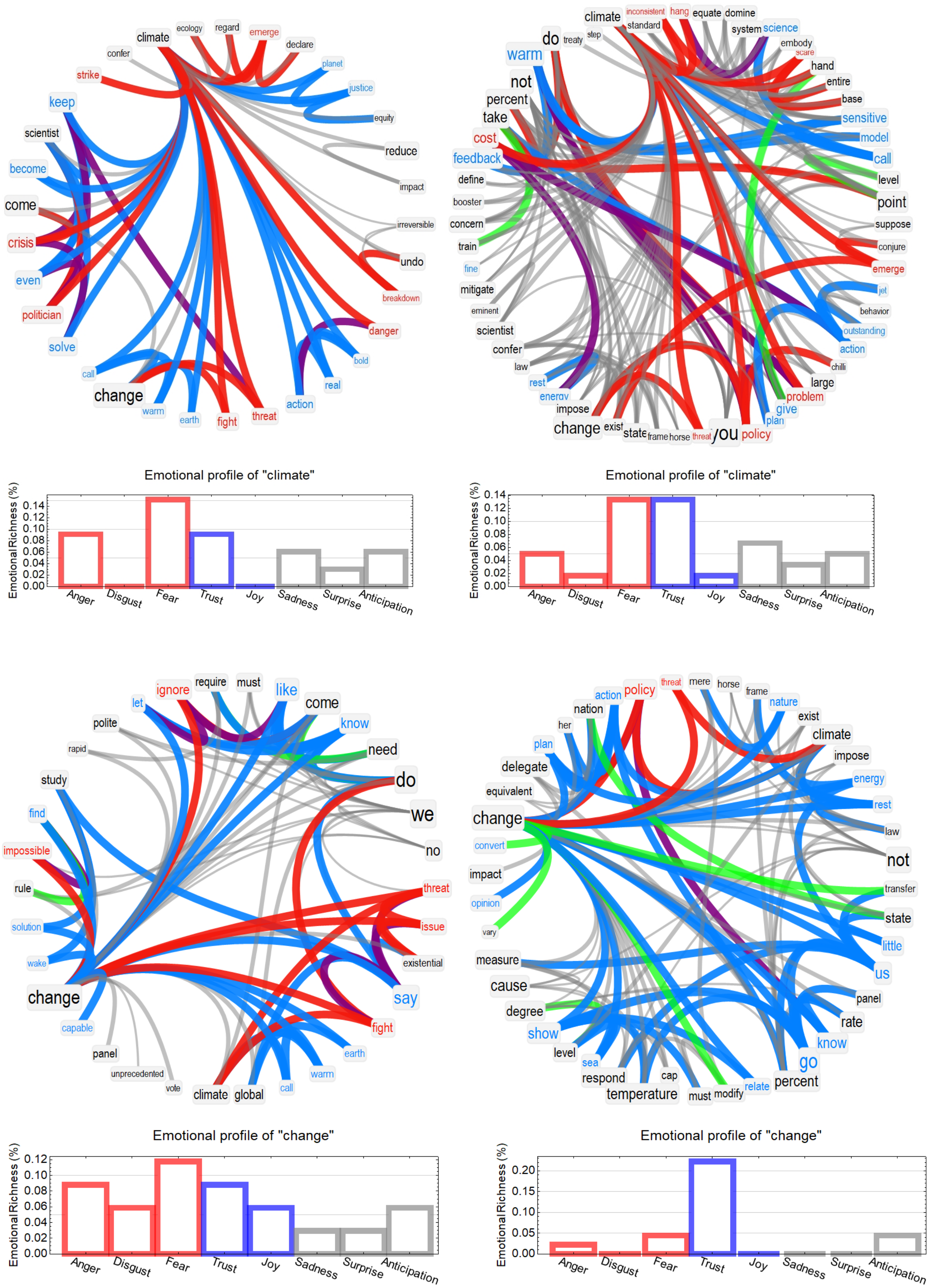

Figure 1. Speakers' mindset reconstruction around "climate" (**top**) and "change" (**bottom**) in the speeches of Greta Thunberg (**left**) and Christopher Monckton (**right**). Links indicate

syntactic and semantic relationships between words in speeches. Links are coloured if linking at least a positive/negative/neutral/synonyms (blue/red/grey/green) word. Blue/red/black (positive/negative/neutral) coloured words indicate how they are perceived in language according to the NRC Emotion Lexicon (see Methods). Font size expresses the relative importance of the words reflecting their centrality in the speeches. Emotions are self-explanatory except for anticipation, which is a projection into future expectations (cf. Stella 2020). We refer the reader to Text Box 1 for an interpretation of the figure.

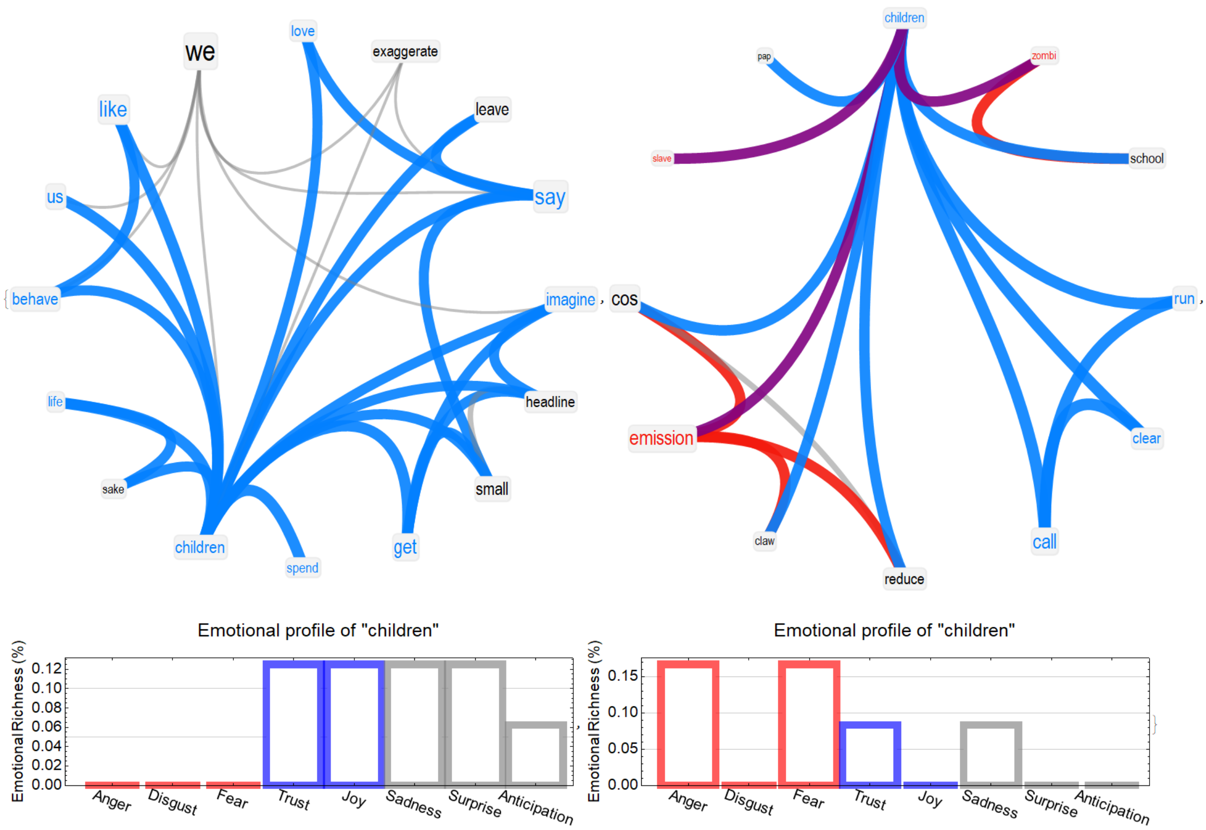

Figure 2. Speakers' mindset reconstruction around "Children" in the speeches of Greta Thunberg (**left**) and Christopher Monckton (**right**). We refer the reader to Figure 1 for a detailed explanation of the colour code, and to Text Box 1 for an interpretation of the figure.

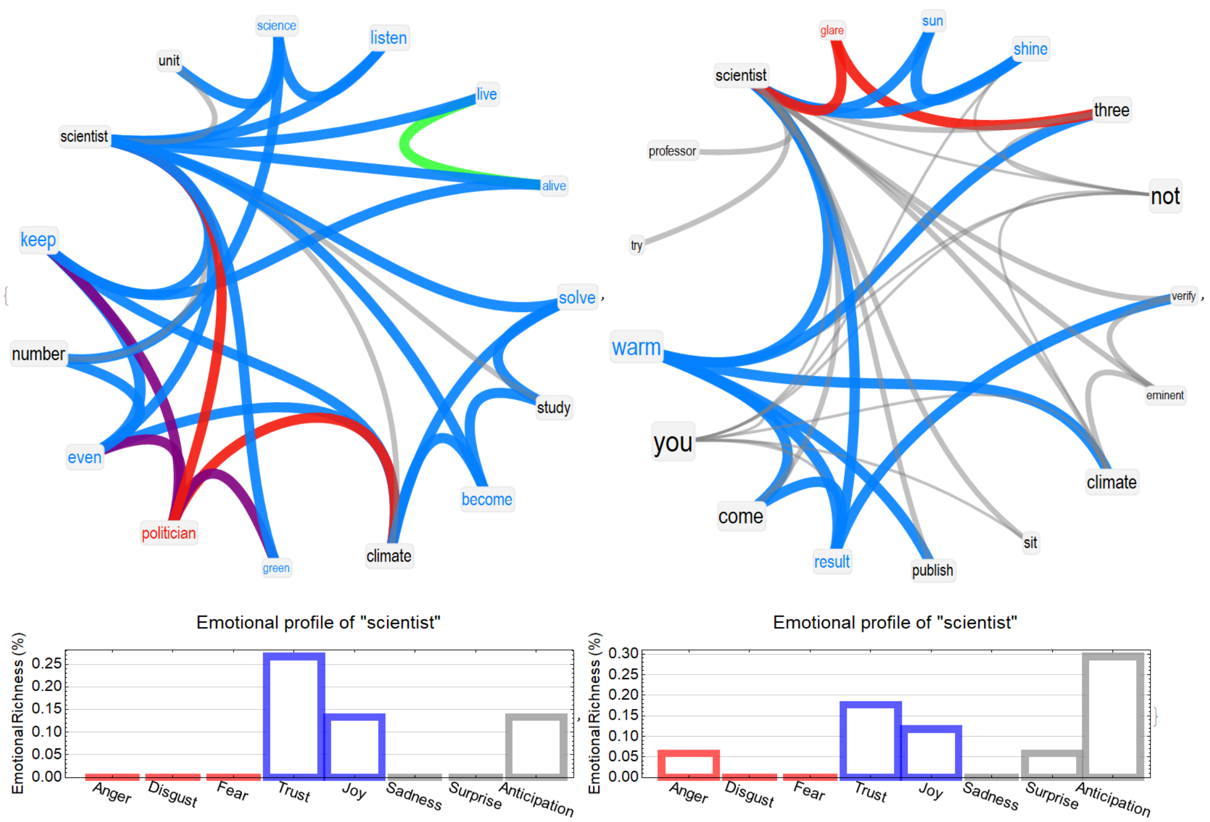

Figure 3. Speakers' mindset reconstruction around "Scientist" in the speeches of Greta Thunberg (**left**) and Christopher Monckton (**right**). We refer the reader to Figure 1 for a detailed explanation of the colour code, and to Text Box 1 for an interpretation of the figure.

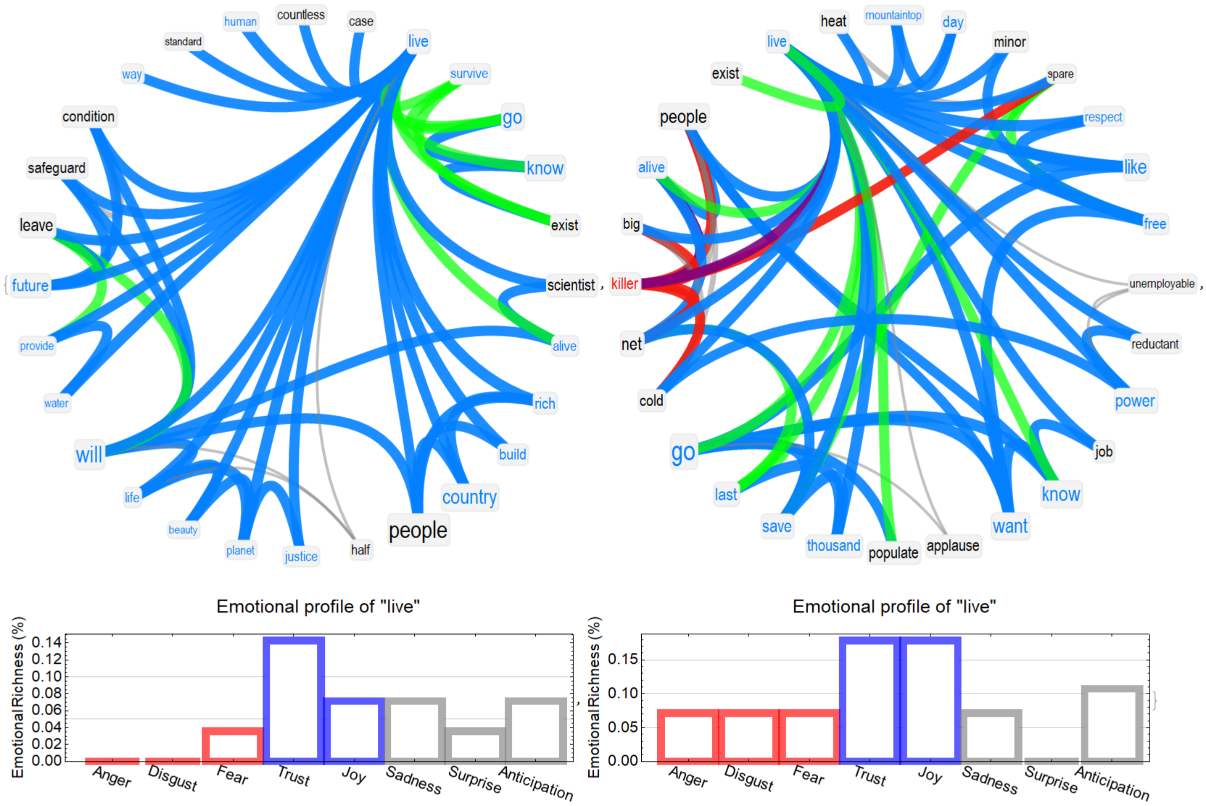

Figure 4. Speakers' mindset reconstruction around "live" in the speeches of Greta Thunberg (**left**) and Christopher Monckton (**right**). We refer the reader to Figure 1 for a detailed explanation of the colour code, and to Text Box 1 for an interpretation of the figure.

Text Box 1: A lexicon of the climate divide, with the associated emotions in both sides.

Action: for climate activism it means hope for a better future, much wanted and needed, propositional toward the elicitation of a revolution-like call to action, while for climate disinformation it is just a sad bureaucratic cost, still something positive but that does not lead to any practical safeguarding initiative (Figures A5 and A10, see Appendix A).

Believe**:** climate disinformation angrily believes there is scarce contradictory evidence, while climate activism's beliefs are strongly propositional about setting goals to avoid the danger of inaction (Figure A6, see Appendix A).

Change: for climate disinformation there is a pattern characterized by trust, low anticipation without risk awareness, overall a perception of "change" that is reassuring, there is no sense of threat, no problem at all, except for some fear about policy changes. For climate activism change is linked to high levels of negative emotions like anger, disgust and fear, related to a perception of existential threats (Figure 1).

Children: an angering concern for climate disinformation. Climate activism perceived children with trust and joy, but sadness for their anticipated future (Figure 2).

Climate: a fearsome threat, linked to inconsistent science for climate disinformation or to scary tipping points for climate activism (Figure 1).

Future: relatively absent in climate disinformation , it inspires trust linked to future awareness in climate activism (Figure A8, see Appendix A).

Ignore: a large and central concept for climate activism, counterfactually associated to trust that people will come to let change happen. Ignore is only peripheral for climate disinformation and linked to trust on the potential profits of global warming (Figure A7, see Appendix A).

Leader: someone to trust and follow in climate disinformation, but who triggers anger linked to "politicians" and "emissions" in climate activism, and still inspires trust (Figure A9, see Appendix A).

Live: climate activism uses this term carefully, associating "live" to trust to conditions of human survival and planetary justice, while climate disinformation does not display a coherent pattern (Figure 4).

Number: climate activism stays positive and lacks objections to numbers coming from current science, while climate disinformation displays an opposite pattern of strong anxiety projecting into the future a sense of exaggerated imbalance in the issues at hand (Figure A11, see Appendix A).

Science: inspiring mostly negative emotions of anger, disgust and fear in climate disinformation, it is a matter of trust associated to listening and numbers for climate activists (Figure A1, see Appendix A).

Scientist: isolated prophets that provide facts for narratives of climate disinformation around changes in solar radiation and that are a source of anticipation. Instead, for climate activism they are people that politicians need to listen to, experts that solve problems (Figure 3).

In their promoted mindsets, climate disinformation resorts to a wide variety of trust-related semantic associates reducing scientists to isolated prophets that provide alternative facts, which they relate to disinformation attempts to convince the public with alternative scientific evidence on global warming. Despite presenting alternative facts, negative emotional associations with “climate” such as “hysteria” and “catastrophe” are only present on climate disinformation, while climate activism gives more relevance to “breakdown”, “danger” and “threat” (Figure A3, see Appendix A).

Anticipation, a projection into the future of both anxiety and excitement, is a stronger emotion for climate activism around concepts of “leadership”, “listen” (Figure A2, see Appendix A), “children” and “threat”. Climate disinformation concentrates anticipation toward “studies” and “numbers”, due to the anxiety that scientific facts create to the climate disinformation community. The emotion of surprise is linked to “children” and “future” (Figure A8, see Appendix A) for climate activism, while climate disinformation associates it to the “numbers” behind climate science. Sadness is very strong in the climate activism arena for concepts like “children”, “action”, or “believe”, and appears also linked to “future”, “climate”, “leader”, and “live”.

Climate disinformation displays high levels of sadness only around the term “believe”. Joy is counterfactually high for terms like “children” and “action” in climate activism, which can be explained by the emotions of hope and sense of belonging to a growing group (Lerner, 2015).

Trust, an emotion strongly used by outstanding visionary leaders (Mumford, 2006), is consistently high for climate activists, with very high values associated to its science-based grounds. Instead, climate disinformation projects trust toward future-centered terms like “change”, “live”, and “study” (Figure A12, see Appendix A), linked to reports with alternative facts from their own dissemination activities.

Fear is higher for terms like “climate change”, “threat”, “issue” (Figure A4, see Appendix A), and “believe” in climate activism, while for climate disinformation fear appears very intense against “children”. Anger again is linked to “children”, and also “believe”, in climate disinformation, while for climate activism anger is associated to “climate change” and “leader”. Last but not least, disgust appears linked to how much both sides “ignore” each other.

Figure 1 (top left) illustrates that climate activism perceived “climate” as overwhelmed by the threat of climate breakdown, whereas climate disinformation associated “climate” with neutral concepts expressing ‘inconsistent science’ (top right). Such dichotomy reverberates in the mental construct of “change”, a neutral concept by itself in common language. In climate activism, “change” was associated to concepts strongly eliciting anger and fear but also trust, an emotion identifying outstanding visionary leaders (Mumford, 2006). Climate activism gave relevance to “breakdown”, “danger” and “threat”, concepts characterising charismatic value-based mindsets (Mumford, 2006) and revolutionary speeches (Jasper 2011; Kramer et al. 2014). Stunningly, in climate disinformation such threatened perception was completely absent (Fig. 1, bottom left) and left space to a wide variety of trust-evoking associates about attempts to convince the public with alternative facts on global warming.

Climate activism combines anger (towards inaction), fear (of an approaching threat) and trust (in solving this crisis), and perceives “climate change” as an indispensable “call-to-action” fight. This “call-to-action” is urgently motivated by a combination of emotions: anger against political leaders, fear for the dangers of inaction and against existential climate threats, disgust about a stolen future, and an overall ambition to act over climate change. This “call-to-action” makes climate activism’s mindset entwined with revolutionary emotions. In fact, emotions like anger, hope and despair are well known to accelerate the social tipping dynamics of large-scale social protests and revolutions (Jasper, 2011).

Furthermore, it is known that outstanding future-focused leaders, often promoters of such revolutions, rely on emotional styles revolving around trust, joy and anticipation (Mumford, 2006), so that detecting these emotions in a future-oriented topic like climate change can provide insights on how charismatic #FridaysForFuture can be. Cognitive and semantic contagion require conscious information processing, e.g. interpretation and acceptance, whereas emotional contagion can lead to a faster transfer of moods among people, involving both implicit and explicit mechanisms (Kramer et al., 2014). Positive emotions like trust and joy have been reported to cause a "ripple effect", i.e., a “pandemic” or “tsunami” of massive contagion of positive sentiment driving the social behaviour of the whole collective in synchrony (Barsade, 2002). In other words, the emotions and perceptions linked to climate activism have been described as rippling better through society, and thus reaching larger social audiences (Jasper, 2011; Mumford, 2006), in comparison to the emotional profile adopted by climate disinformation.

In fact, conceptual associations and emotions indicate that climate disinformation promotes hypercritical scepticism, hiding under a generally trustful promotion of change and including: (i) discussing numbers in terms of imbalanced exaggerations, (ii) referring to scientists in a stereotypical way, i.e. isolated individuals that attempt to provide abstract, theoretical evidence to climate disinformation, (iii) displaying negative emotions against children, and (iv) showing fear against public policy interventions. These hypercritical attitudes clash with the communication style of the *#FridaysForFuture* movement, which Marris (2019) describes as projecting greater moral integrity due to a lack of immediate vested interests.

As reported in the semantic-emotional analysis around other concepts (see the lexicon reconstructed in Text Box 1), climate disinformation displays high levels of sadness only around the term “believe”. Joy is counterfactually high for terms like “children” and “action” (Figure A5, see Appendix A) in climate activism, which can be explained by the emotions of hope and sense of belonging to a growing group (Lerner, 2015).

These hypercritical attitudes disrupt public awareness on the climate emergency and compromise public consensus to stabilize Earth’s climate (Bloodhart, 2019). They prevent policy-makers from acting over the risks posed by climate change (Hoffman, 2011; Watts et al. 2020). Thus, they obstruct the Paris Agreement and the formation of foreseen social tipping dynamics towards decarbonization (Otto et al. 2020).

4. Discussion and Conclusion.

We have shown that applying network science to textual content and analysing the emerging mindset can support research about infodemics, i.e. the quick and pervasive spread of falsehoods. We have identified disinformation emotional patterns, such as hypercritical scepticism masked under a trustful promotion of change. The reconstructed mindsets and the emotional patterns identified provide new pointers on climate disinformation.

Climate disinformation sustains a chain reaction triggering a major divide at the global scale, which threats sustainability, human health and ultimately the global economy (Hoffman, 2011). Infodemics strongly depend on their emotional and perceptual content, much like viruses spreading across populations according to their genetic information. Recent studies highlighted how contagions of distorted perceptions and misinformation greatly influence human responses to the climate threat (Bloodhart, 2019).

Emotions and their contagion, much like a pathogen spreading over societies (Kramer et al. 2014), have been instrumental in large-scale societal changes like revolutions from Maoist China to Nicaragua and Czechoslovakia (Jasper, 2011), and are instrumental in the process of emergence of charismatic social and political leaders (Mumford, 2006). Nevertheless, the parallelism in the emotional patterns of a revolution could be just anecdotal. As a matter of fact, the call to action by #FridaysForFuture is limited to policy-making. And objectively, the movement often finds a “glass ceiling” about how they could trigger change beyond their demonstrations and judicial actions (Neubauer, 2019).

Tracing this emotional parallelism with massive social movements is important because recent calls to civil disobedience by leading climate diplomats (Figueres and Rivett-Carnac, 2020) could create game-changing developments if related to large-scale emotional contagions, but could be hindered by disinformation. These interactions between propelling and hindering factors points us towards future work on the opinion dynamics of the climate divide, within and between sides.

Despite the amount of meaning found in the results, and the showcased pointers to identify misinformation via emotions, a more detailed analysis focussing on a larger set of relevant leaders by world region — including more subjects from a diversity of geographies — would improve the depth of the insights and their potential for representativeness.

Given also recent converging evidence of positive emotions fostering engagement with policies tackling climate change (Schneider et al. 2021), the methods outlined in here might have significant impact over detecting positive affect and emotions in next-generation communication efforts rallying actions about the climate emergency. Nevertheless, the availability of emotional dictionaries is often limited to the English language, which sets a barrier when working on other languages.

We conclude that mindset reconstruction could be an important tool to deal with disinformation communication materials facilitating the climate divide. Mindset reconstruction of textual content provides a scientific basis for detecting climate-related hypercritical attitudes and fuelling discourses. Hence, mindset reconstruction could help to design strategies narrowing the climate divide by countering infodemics in climate-related communication. The innovative techniques we have shown — at the fringe of AI and cognitive science — could support climate policy in multiple ways, like: (i) flagging online communication materials containing conceptual associations distorted by disinformation content (Hills 2019), (ii) highlighting key sources of emotions commonly adopted by supporters of the climate divide, complementing recent human coding approaches to emotion detection in climate change debate (Hahnel et al. 2020), and (iii) measuring levels of trust in the specific semantic frames surrounding large institutions and expressed in massive social media debates about climate change (Marris 2019). Further work includes the automated training of cognitive tools for in-vivo flagging of online disinformation content in several languages, and the study of their influence on the opinion dynamics of pro-active climate debates.

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Author contributions:

R.C. and M.S. envisioned the study. M.S. and R.C. collected the data and analysed it. R.C. and M.S. drafted the manuscript.

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Appendix A.

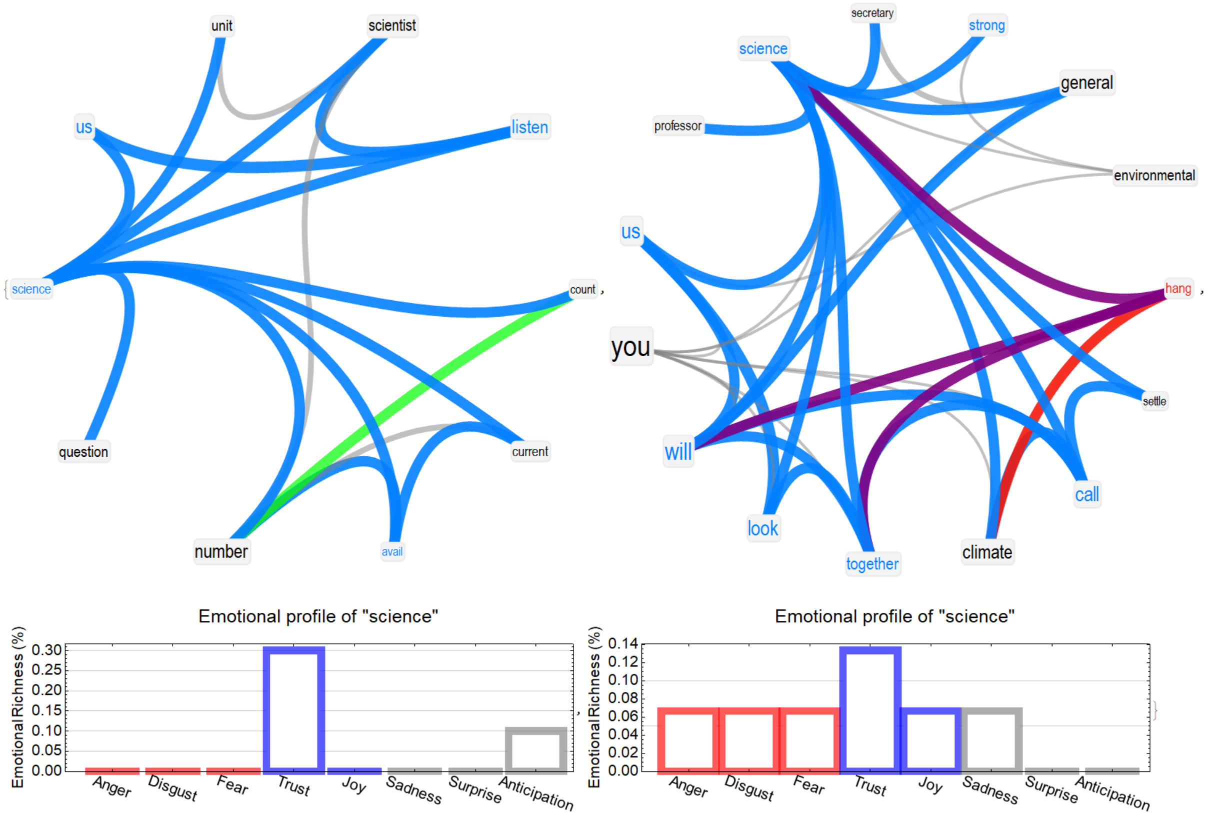

Figure A1. Speakers' mindset reconstruction around "Science" in the speeches of Greta Thunberg (**left**) and Christopher Monckton (**right**). We refer the reader to Figure 1 for a detailed explanation of the colour code, and to Text Box 1 for an interpretation of the figure.

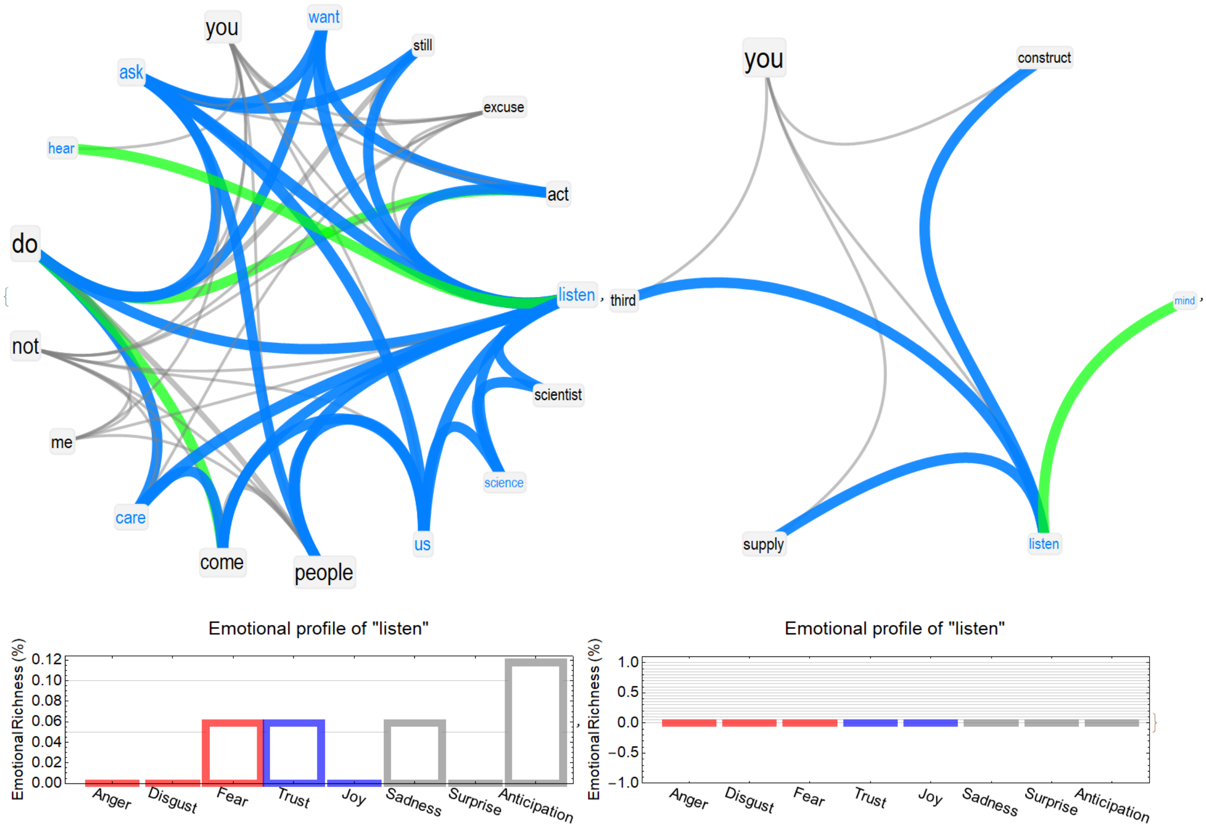

Figure A2. Speakers' mindset reconstruction around "listen" in the speeches of Greta Thunberg (**left**) and Christopher Monckton (**right**). We refer the reader to Figure 1 for a detailed explanation of the colour code, and to Text Box 1 for an interpretation of the figure.

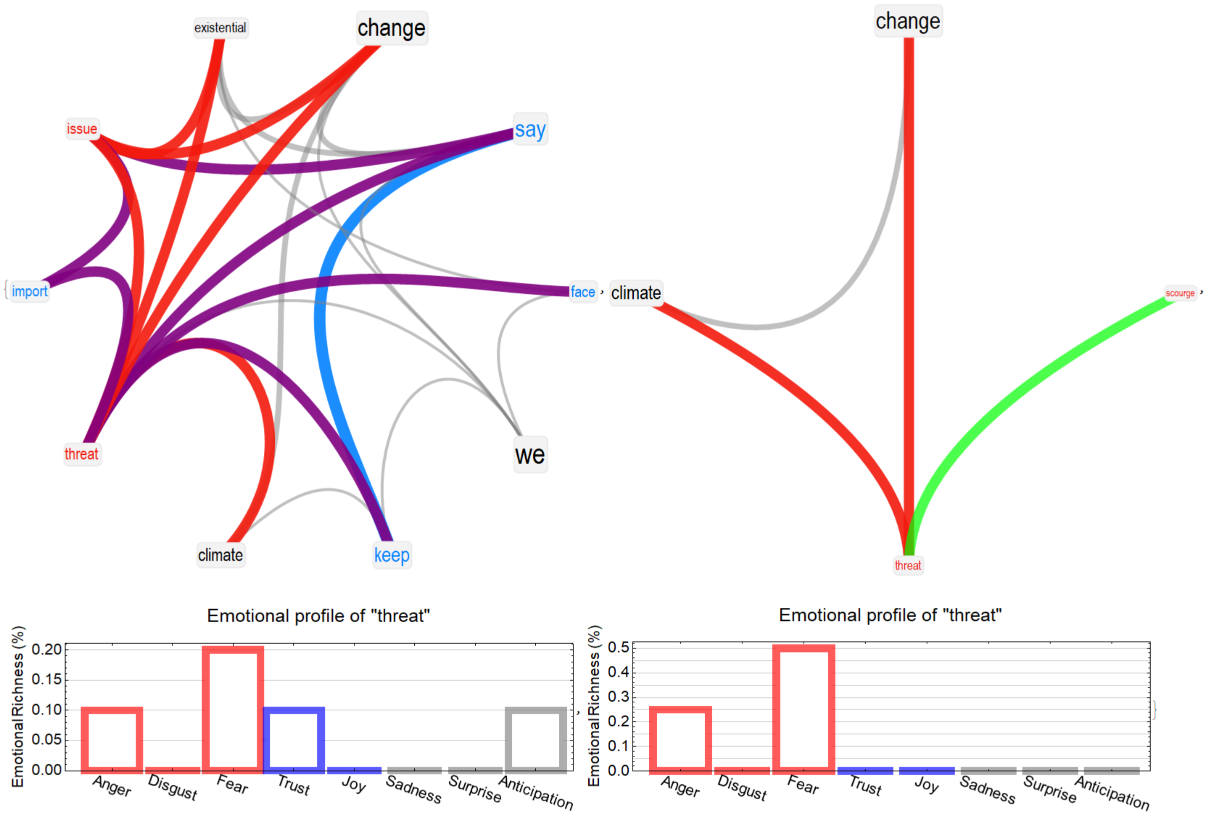

Figure A3. Speakers' mindset reconstruction around "threat" in the speeches of Greta Thunberg (**left**) and Christopher Monckton (**right**). We refer the reader to Figure 1 for a detailed explanation of the colour code, and to Text Box 1 for an interpretation of the figure.

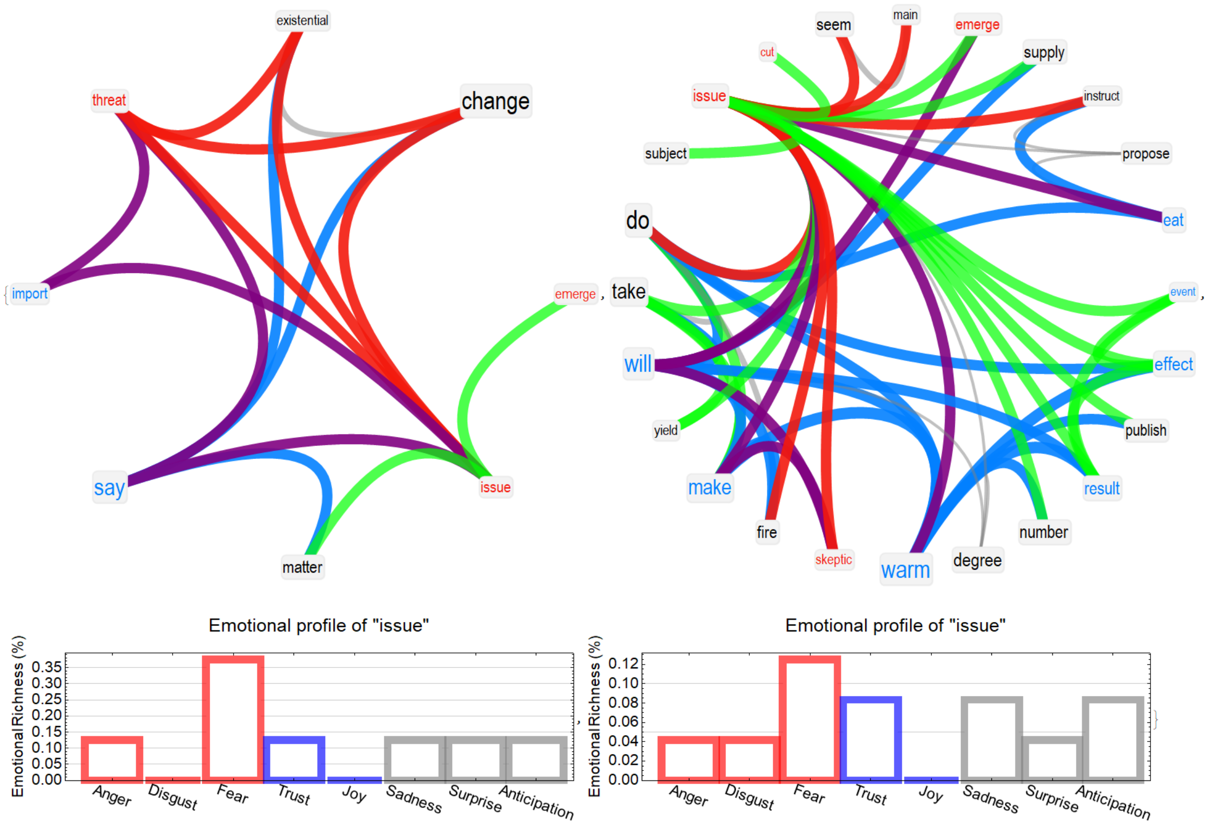

Figure A4. Speakers' mindset reconstruction around "issue" in the speeches of Greta Thunberg (**left**) and Christopher Monckton (**right**). We refer the reader to Figure 1 for a detailed explanation of the colour code, and to Text Box 1 for an interpretation of the figure.

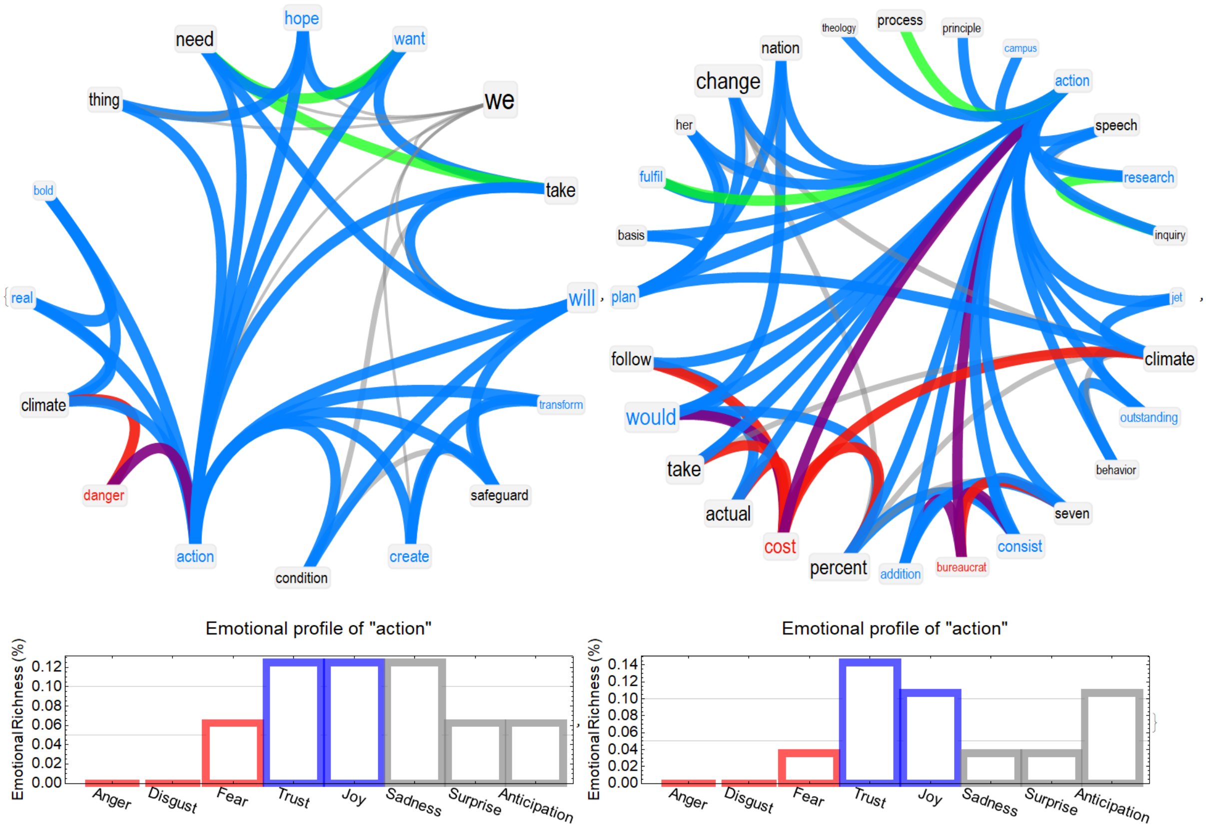

Figure A5. Speakers' mindset reconstruction around "action" in the speeches of Greta Thunberg (**left**) and Christopher Monckton (**right**). We refer the reader to Figure 1 for a detailed explanation of the colour code, and to Text Box 1 for an interpretation of the figure.

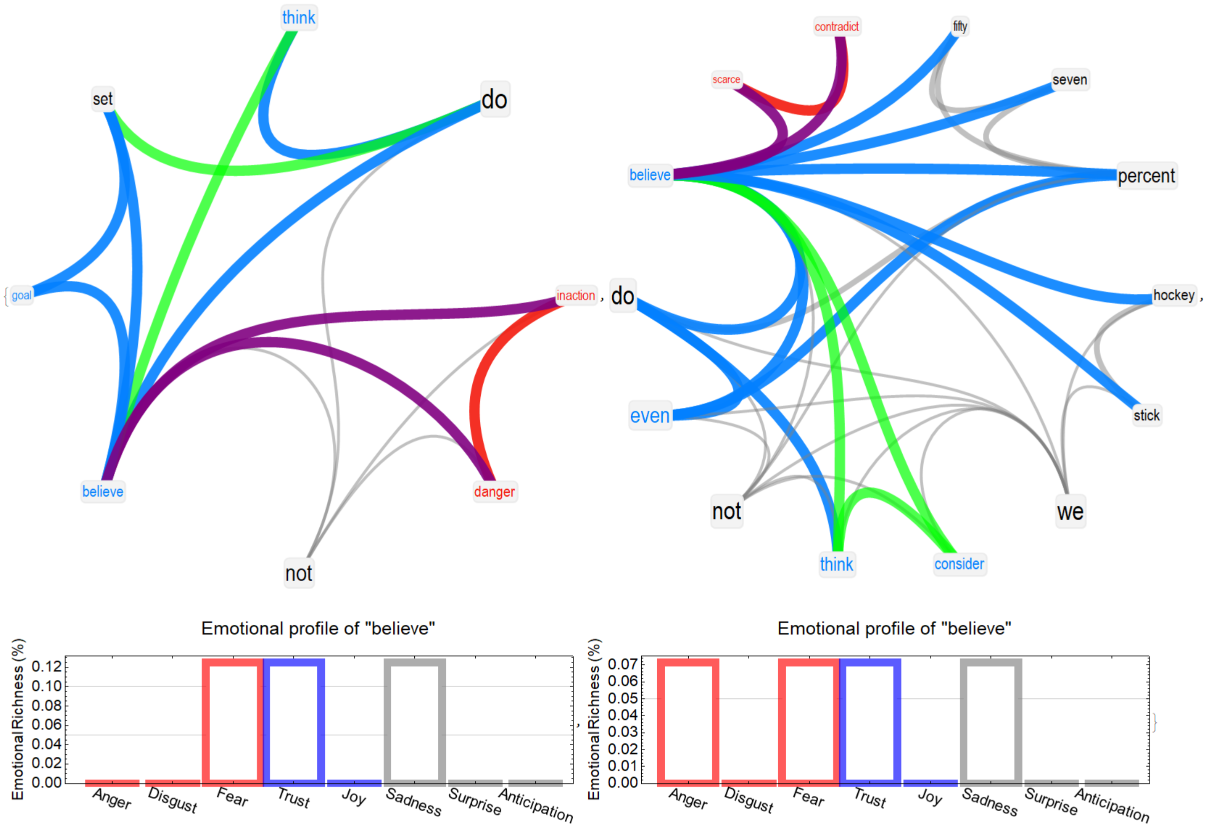

Figure A6. Speakers' mindset reconstruction around "believe" in the speeches of Greta Thunberg (**left**) and Christopher Monckton (**right**). We refer the reader to Figure 1 for a detailed explanation of the colour code, and to Text Box 1 for an interpretation of the figure.

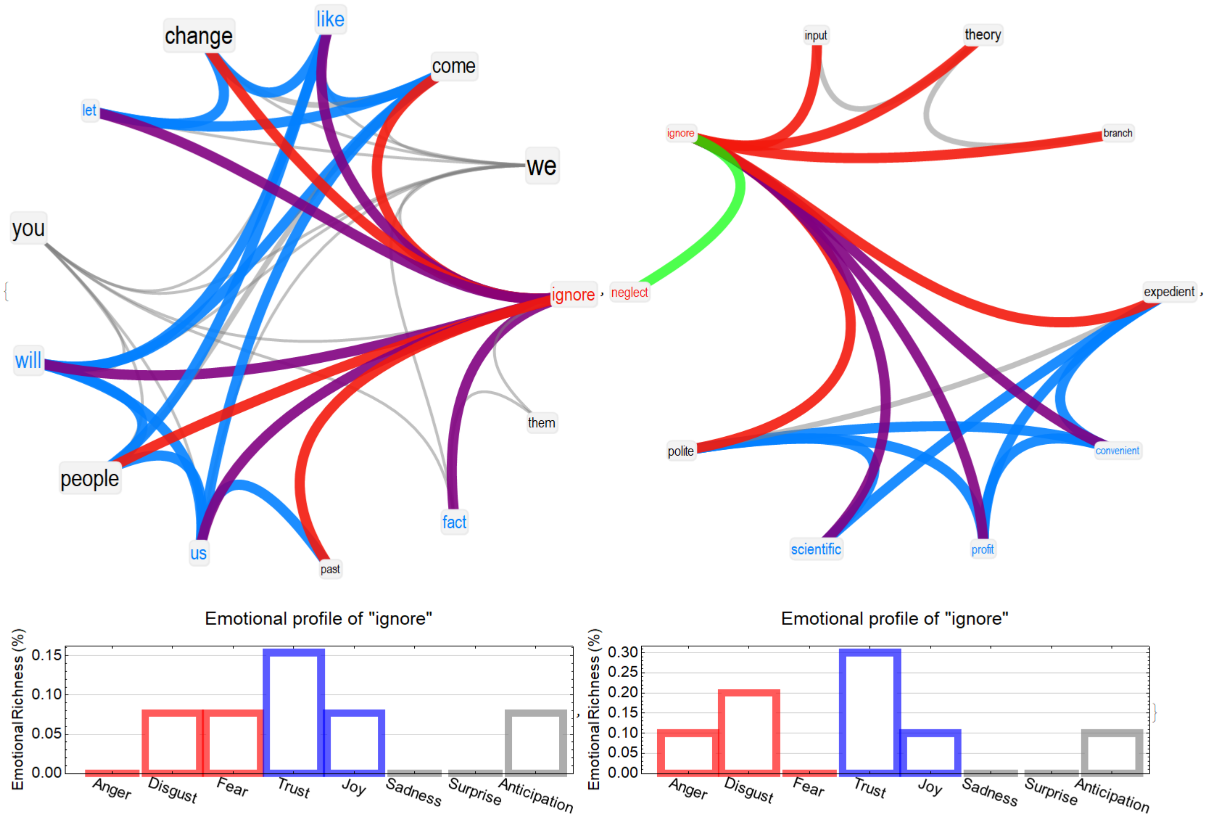

Figure A7. Speakers' mindset reconstruction around "ignore" in the speeches of Greta Thunberg (**left**) and Christopher Monckton (**right**). We refer the reader to Figure 1 for a detailed explanation of the colour code, and to Text Box 1 for an interpretation of the figure.

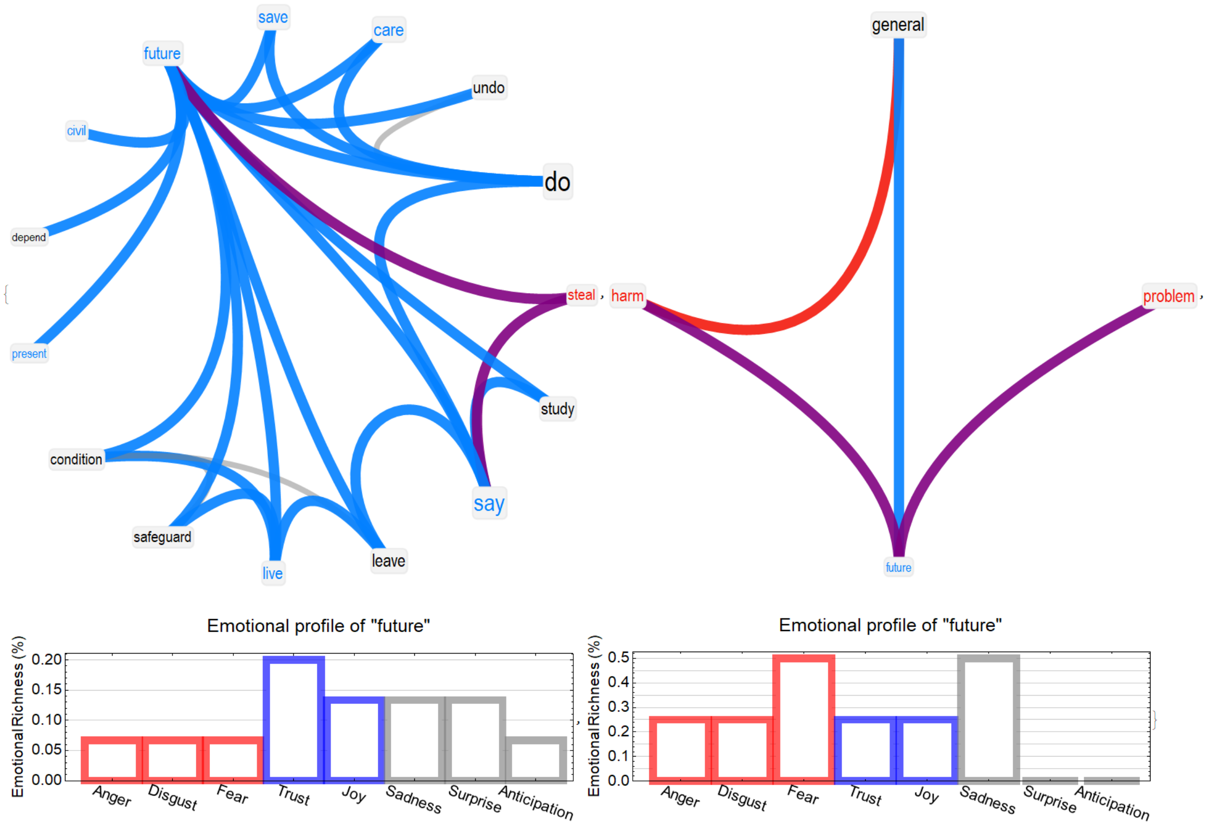

Figure A8. Speakers' mindset reconstruction around "future" in the speeches of Greta Thunberg (**left**) and Christopher Monckton (**right**). We refer the reader to Figure 1 for a detailed explanation of the colour code, and to Text Box 1 for an interpretation of the figure.

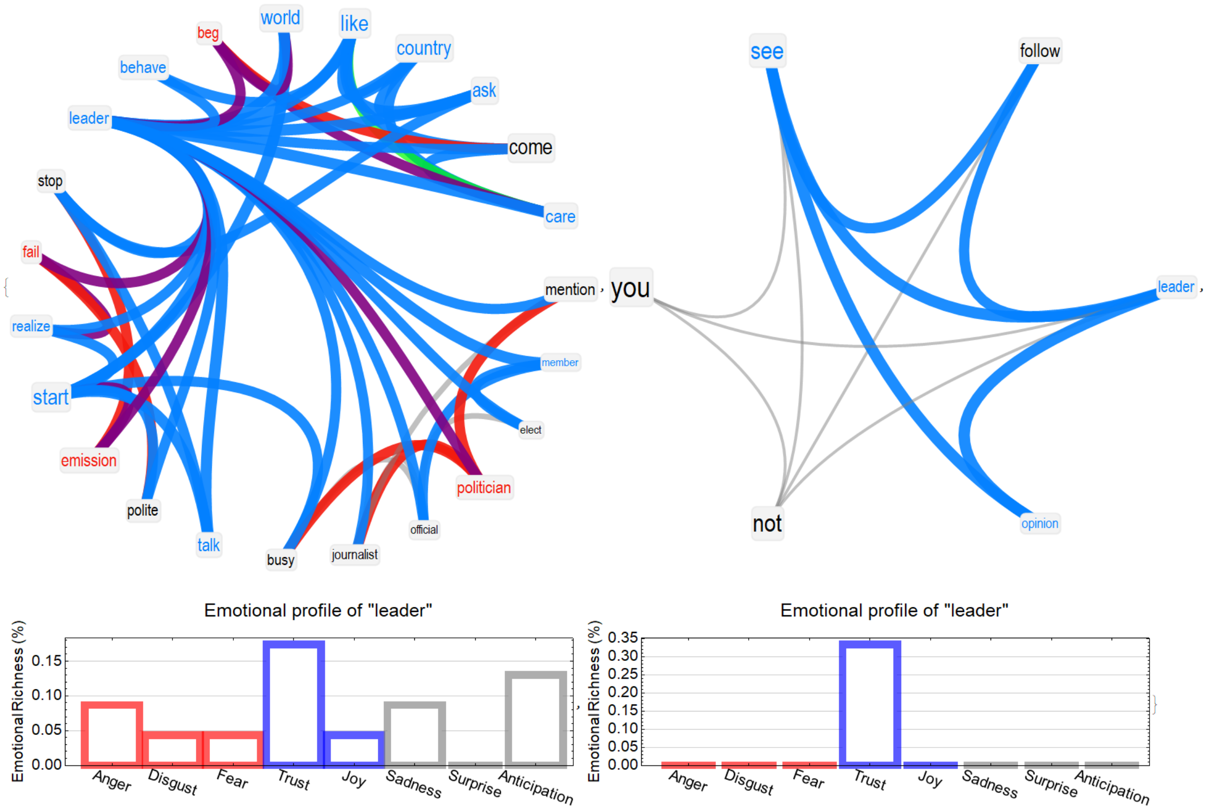

Figure A9. Speakers' mindset reconstruction around "leader" in the speeches of Greta Thunberg (**left**) and Christopher Monckton (**right**). We refer the reader to Figure 1 for a detailed explanation of the colour code, and to Text Box 1 for an interpretation of the figure.

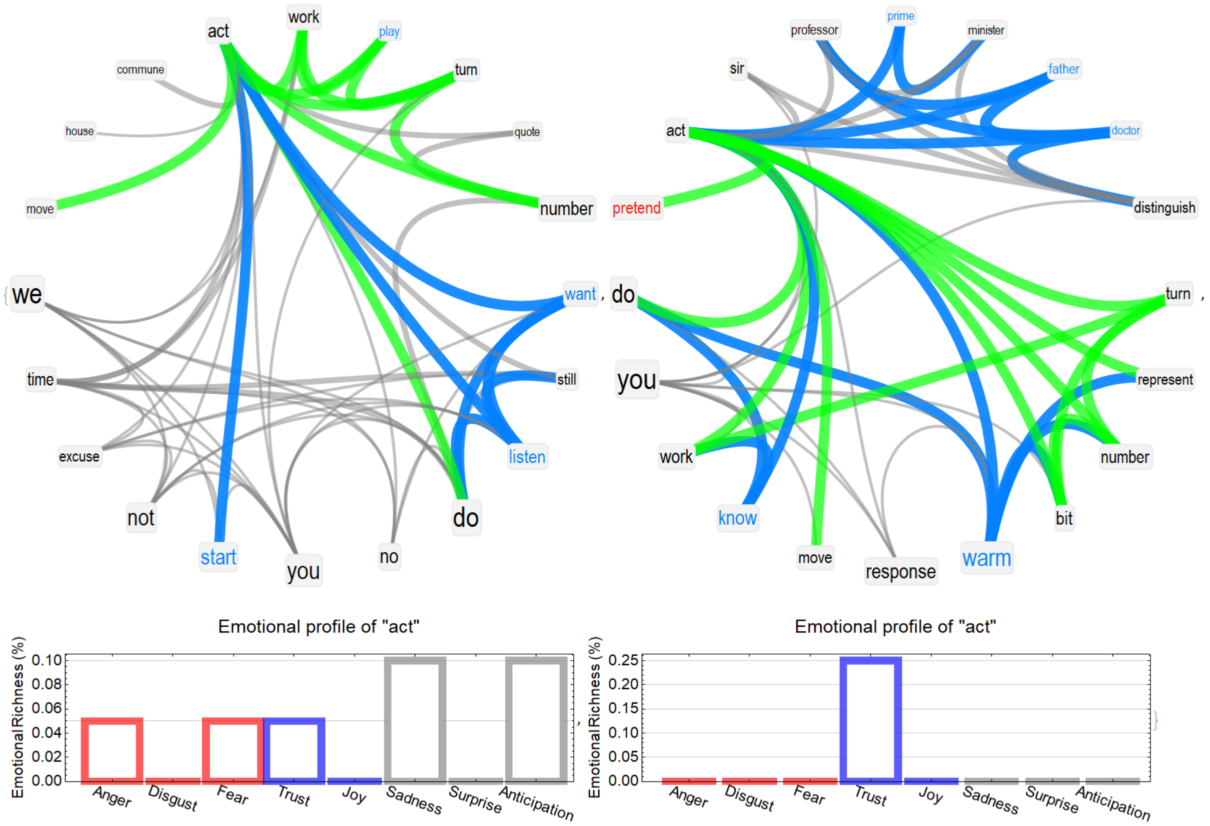

Figure A10. Speakers' mindset reconstruction around "act" in the speeches of Greta Thunberg (**left**) and Christopher Monckton (**right**). We refer the reader to Figure 1 for a detailed explanation of the colour code, and to Text Box 1 for an interpretation of the figure.

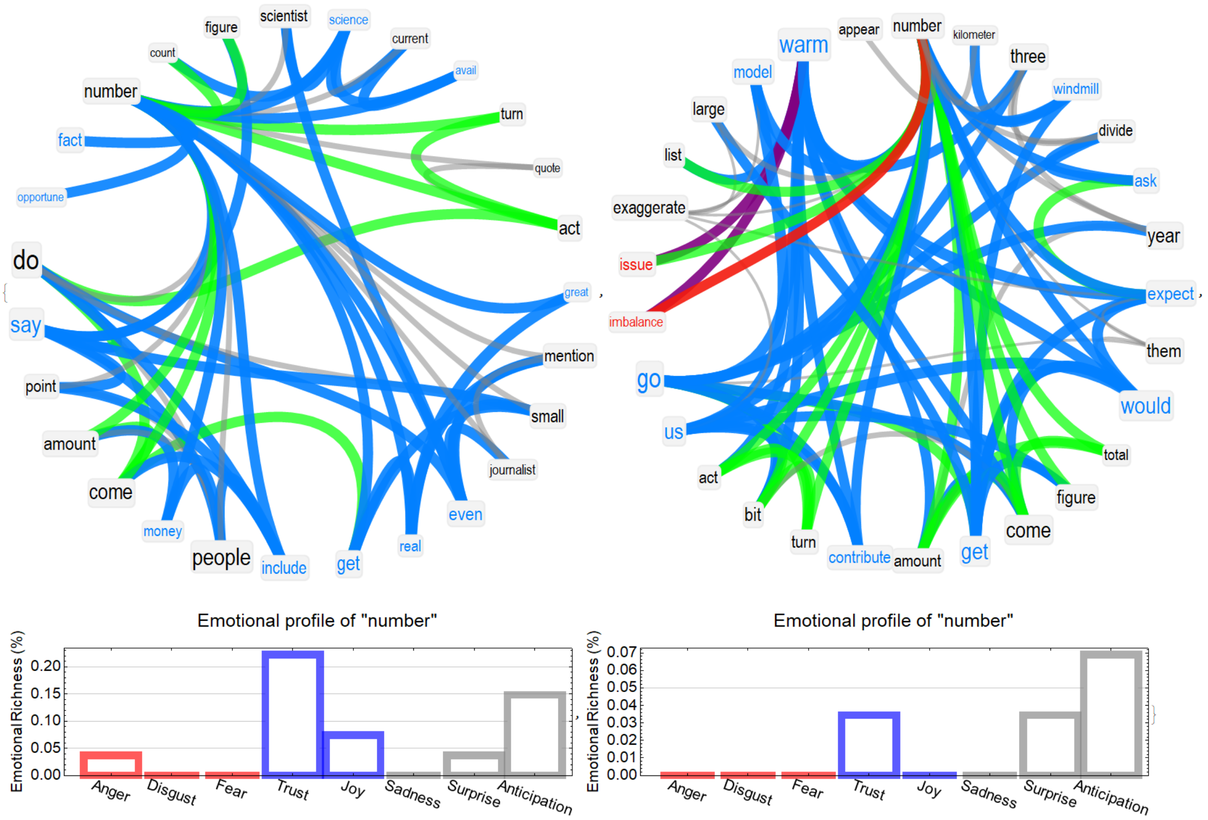

Figure A11. Speakers' mindset reconstruction around "number" in the speeches of Greta Thunberg (**left**) and Christopher Monckton (**right**). We refer the reader to Figure 1 for a detailed explanation of the colour code, and to Text Box 1 for an interpretation of the figure.

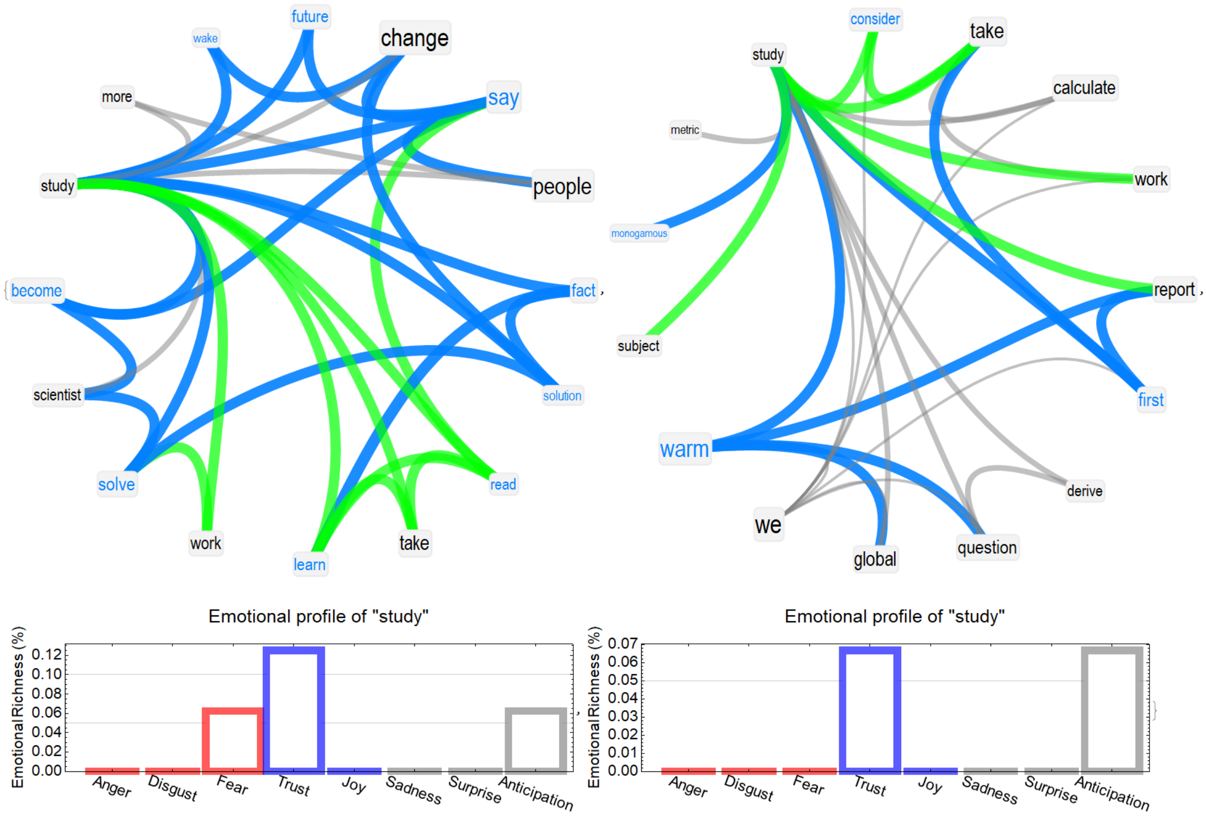

Figure A12. Speakers' mindset reconstruction around "study" in the speeches of Greta Thunberg (**left**) and Christopher Monckton (**right**). We refer the reader to Figure 1 for a detailed explanation of the colour code, and to Text Box 1 for an interpretation of the figure.