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## Stills: Functional Brain Network Organisation Patterns in the Understanding of Text


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# *Zusammenfassung*

Diese Arbeit untersucht, wie die textbasierte Sinnfindung aus der Perspektive des Gehirns betrachtet werden kann, das als dynamisches, sich selbst organisierendes System verstanden wird, das in fortlaufende Beziehungen zwischen Akteur und Umwelt eingebettet ist. Auf empirischer Ebene verfolgt sie Veränderungen in der Organisation großräumiger funktioneller Hirnnetzwerke während der Auseinandersetzung mit klimabezogenen Aussagen, die als bedrohungsorientiert, lösungsorientiert und neutral formuliert sind. Zur Untermauerung der Interpretation neuronaler Daten wird ein von der Enaktivismus-Theorie inspirierter theoretischer Rahmen entwickelt, in dem der Ort der Kognition den Beziehungen zwischen Gehirn, Körper und Umwelt zugeschrieben wird. Als Werkzeuge mit kompatiblen relationalen, dynamischen und systemischen Ausrichtungen kommen graphentheoretische Analysen und Co-Aktivierungsmuster-Analysen (CAP) zum Einsatz.

Die Ergebnisse lassen kein einheitliches neuronales Bild erkennen, das es ermöglichen würde, dem Zustand die damit verbundene kognitiv-affektive Verschiebung zuzuschreiben. Die graphentheoretische Analyse zeigt eine geringere globale funktionelle Netzwerkintegration bei der Auseinandersetzung mit explizit klimawandelbezogenen Aussagen im Vergleich zu neutralen Aussagen, was auf eine verminderte topologische Integration hindeutet, wenn sich die Teilnehmer mit Aussagen befassen, die sie als affektiv markanter empfanden. Gleichzeitig zeigt die CAP-Analyse einen moderaten Kontrast zwischen bedrohungs- und lösungsorientierten Bedingungen mit einem höheren Auftreten eines vorübergehenden Zustands, der vorläufig als Indikator für Handlungsbereitschaft interpretiert werden könnte. Auf der Grundlage der entwickelten theoretischen Ansätze wird dieser Zustand als vorläufiges neuronales Merkmal eines über Zeit und Subjektivität hinweg ausgedehnten Körpers interpretiert.

Ein bemerkenswertes Ergebnis war die beträchtliche interindividuelle Variabilität der Verläufe der Graphenmetriken, wobei sich bei den Teilnehmenden unterschiedliche und sogar gegensätzliche, auf die jeweilige Situation bezogene Muster zeigten. Das zugrunde liegende Verständnis des Textes ist nicht nur der kommunikative Rahmen. Der aktuelle Zustand des Lesers, einschließlich individuell unterschiedlicher neuronaler Dynamiken, ist eine mitbestimmende Variable. Diese Variabilität wird als theoretisch aufschlussreiches Merkmal der empirischen Daten angesehen und weist auf die Notwendigkeit künftiger Forschung hin, die diese Variabilität nachzeichnet, anstatt sie durch Mittelwertbildung zu vernachlässigen.

# Abstract

This thesis examines how text-based sense-making may be approached from the perspective of the brain understood as a dynamic, self-organising system embedded in ongoing agent–environment relations. On an empirical level, it traces changes in large-scale functional brain network organisation during engagement with climate-related statements framed as threat-oriented, solution-oriented, and neutral. An enactivist-inspired theoretical framework is developed to ground the interpretation of the neural data, where the locus of cognition is ascribed to brain-body-environment relations. Graph theoretical and co-activation pattern (CAP) analyses are employed as tools with compatible relational, dynamic, and systems-level orientations.

Results do not converge on a unified neural picture that would allow one to ascribe the condition its associated cognitive-affective shift. Graph theoretical analysis reveals lower global functional network integration during engagement with explicitly climate-change-related statements compared to neutral ones, suggesting reduced topological integration when engaging with frames that participants reported as more affectively salient. Meanwhile, CAP analysis shows modest contrast between threat- and solution-oriented conditions with a higher occurrence of a transient state that tentatively may be interpreted to index action-readiness. Drawing on the developed theoretical lines, this state is interpreted as a tentative neural signature of a body extended across time and subjectivity.

A notable finding was the considerable inter-individual variability in graph metric trajectories, with varied and even opposing condition-related patterns across participants. The underlying understanding of the text is not just the communicative frame. Reader's ongoing state, including individually varied neural dynamics, is a co-constituting variable. This variability is taken as a theoretically informative feature of empirical data, gesturing towards the need for future research that traces rather than averages it away.

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# *Contents*

# 1
# *Introduction*

> *Whether or not he wills it, man is the technician of the human species.*
>
> —Simondon 2015, p.18 (1759)

2024 was the warmest year on record, with ocean heat content hitting new highs and Antarctic sea ice reaching historic lows (WMO 2025). It is not surprising that every discipline, as a dutiful citizen, is invited to contribute to tackling the impending crisis. Regarding neuroscience, Doell et al. (2023) propose four ways to leverage the discipline's reach: "(1) investigate the negative impact of climate change on the human brain; (2) identify ways to adapt; (3) understand the neural substrates of decisions with pro-environmental and harmful outcomes; and (4) create neuroscience-based insights into communication and intervention strategies that aim to promote climate action". The current study examines functional large-scale brain network configurations during engagement with climate-related statements. And while the focus of the paper lies on the cognitive process, given the climate-related content of the text statements, I want to register caution from the onset regarding the potential presumption that the work is presented to supply neural-based insights in how to tackle the looming crisis.

### *1.0.1 Reflexive Turn: Critical Neuroscience*

Behavioural and brain sciences have systematically been co-opted into i-frame thinking — framing policy problems in individual, rather than systematic terms (s-framing) (Chater and Loewenstein 2023). This tendency is also visible in climate neuroscience, where investigation of neural correlates of pro-environmental choice inevitably keeps attention on the individuals while structural causes go unaddressed. As the case was made by Moser (2016) and Shove (2010), decades of communication and behaviour-change research have not produced commensurate real-world impact precisely because, by and large, barriers are institutional. Following, framing climate inaction as a neuroscientific problem is not a neutral scientific move but one with political valence that risks *depoliticising* a structural issue into a brain 'fact'.

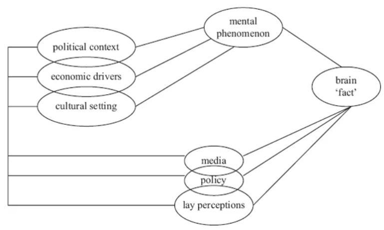



Figure 1.1: The journey of the 'brain fact'. Taken from (Choudhury, Nagel et al. 2009).

**Existing Literature: Framing Effects in Climate Communication**

From a psychological lens, lack of the individual action in response to climate change has been partially credited to the perception of climate change as a psychologically distant problem (Van Lange and Huckelba 2021; S. Wang et al. 2021). Following such argumentation, suggestion is that reducing said distance in climate communication, by presenting the consequences as closer in time and to the self, could make the environmental problems feel less abstract and promote positive climate action. Evidence for the effectiveness of such a strategy, however, seems to be mixed (Maiella et al. 2020). A large-scale international study by (Vlasceanu et al. 2024) concluded that while psychologically close framing of climate change information enhanced belief in the reality of climate change, the increase was modest. Further, neither framing aimed at reduced psychological distance nor ten other messaging interventions increased people's motivation to engage in climate-mitigation behaviours.

Regarding valence framing, a systematic review by Homar and Knežević Cvelbar (2021) suggests that in general, negative/loss frames tend to be more effective than positive/gain frames for increasing pro-environmental intentions and behaviours. Gain framing emphasising the positive benefits of climate-friendly actions while beneficial in certain situations, in general, seem to be more effective at shaping opinions on a topic rather than driving actual behavioural shifts. Further, loss-framed appeals tend to be more persuasive for psychologically proximate environmental issues, whereas gain-framed appeals are more effective for psychologically distant ones. War metaphors, in particular, have been shown to heighten the sense of urgency surrounding an issue (Flusberg, Matlock et al. 2017). Overall, it seems that in climate communication, hitting the right emotional tone is a balancing act, highly dependent on the context of the message. As summarised by Flusberg, Holmes et al. (2024, p. 43):

> First, emotions play a critical but nuanced role. Negative feelings, including a sense of urgency, fear, and concern about the future, are especially motivating. But too much negativity is counterproductive. Dire messaging about climate change has been shown to backfire, reducing belief in global warming by threatening people's sense that the world is a just place (Feinberg & Willer, 2011). Strong negative emotions can also undermine feelings of efficacy and promote the sense that nothing can be done to address environmental devastation. Therefore, positive feelings, such as a sense of hope, are important (Geiger et al., 2023; Nabi et al., 2018), although too much optimism can make the potential impact of climate change on our own lives seem insubstantial (Hornsey & Fielding, 2016). Taken together, this work suggests that environmental messages should be carefully crafted to elicit the right balance of emotional response.

More than a decade ago, Choudhury, Nagel et al. (2009, p. 61) presented a framework for doing critical neuroscience: "a reflexive scientific practice that responds to the social, cultural and political challenges posed by the advances in the behavioural and brain sciences". The overarching aim was not the critique itself but a better empirical neuroscience. Historical, technical, conceptual, ethnographic, social and cultural analyses, study of public engagement in science, identification and tracking of economic influences were, in the end, presented as pursuits to be integrated into the actual scientific practice—to guide how critical neuroscience is done in the lab. Practice-orientation also led critical neuroscience to adopt explicit commitments in treating "brain and cognition as situated and contingent" (Choudhury and Slaby 2011, p. 4).

This commitment finds its philosophical expression in the family of approaches known as the 4E framework, where each E refers to the embodied, embedded, extended, and enacted facets of cognition. Enactivism, encompassing the other E dimensions and opening one of its own also provides theoretical grounding for the present study.

### *1.0.2 Present Study: Aims and Explorations*

The present work is empirically grounded in the fMRI data obtained from an experiment, where participants were exposed to climate-related statements framed as either solution-oriented, threat-oriented, or neutral. For the most part, the current paper follows a conventional academic structure: the introduction is followed by a theory section, which in turn gives way to methods, results, and discussion, before concluding with a brief summary [1]. The main departure from the standard empirical format lies in the prominence given to theoretical development.

[1] This structure was kept for comprehensibility. However, I would also encourage alternative readings. For example, one could start from the conclusion, turn to methods, go to results, move back to theory, and then visit the discussion with a second reading of results.

The extended theory section serves a dual purpose. First, it aims to showcase how enactivist-inspired philosophy informs the choice of analytical tools that allow us to study the brain as a dynamic, large-scale system rather than a collection of anatomically and functionally isolated regions. In this context, graph theoretical and co-activation pattern (CAP) analyses are put forward as available tools whose relational, dynamic, systems-level orientations are responsive to theoretical framing. Second, the enactivist-inspired framework situates the inevitably methodologically constrained findings within a broader cognitive context.

The overarching aim of this approach is methodological as much as theoretical—to study cognition relationally. The present study, specifically, explores:

***How text-based sense-making may be examined from the perspective of the brain understood as a dynamic, self-organising system embedded in ongoing agent–environment relations?***

On an **empirical** level, it examines *whether threat-oriented, solution-oriented, and neutral climate-related communicative frames are associated with distinct patterns of large-scale functional brain network organisation during exposure to climate-related statements*. On a **theoretical** plane, it asks *how such empirical patterns can be interpreted within a framework in which cognition is understood as an emergent process of agent–environment coupling unfolding across ecological, social, and historical dimensions*[2].

[2] The theoretical and methodological approach adopted in this thesis is intentionally eclectic, and not all tensions and contradictions are resolved. But bringing different ideas into dialogue, even if not every thread can be fully worked out, is a necessary orientation in cognitive science, insofar as its object of study remains *cognition*.

Regarding empirical results, exploratory graph theoretical and CAP analyses reveal findings suggestive of condition-related differences in large-scale brain network organisation. However, observed patterns are inconsistent across measures and do not lend themselves to a single interpretation. Graph theoretical analysis points to lower global functional-network integration during engagement with explicitly climate-change-related statements (threat-oriented and solution-oriented) relative to neutral statements. CAP analysis, meanwhile, shows only modest contrast between threat- and solution-oriented conditions, with the latter characterised by a higher occurrence of a transient state that, based on its functional network profile, could be interpreted to index action-readiness. Taken together, the two methods appear to capture different adaptive aspects of engagement with the text — traces of differently organised forms of sense-making rather than stable neural signatures tied to specific communicative framings.

One of the more notable incidental findings is the considerable inter-individual variability observed in graph metric trajectories, showcasing varied and even opposing condition-related functional network organisation patterns across participants. Approached from an enactivist-inspired perspective, this variability represents a promising avenue toward an empirically grounded account of individual history-dependent dynamics. That said, this line of inquiry remains to be pursued in future work.

The suspected individual variability also indicates a limitation of approaches that describe large-scale brain dynamics primarily in terms of temporally and group-averaged summary measures. Further, it highlights the unresolved challenges in operationalising 4E-inspired ideas in interpreting lab-experiment derived data and the need for a more rigorous statistical and formal framework when such a feat is attempted. This study is exploratory and necessarily limited in scope, but it is offered as a theory-reflexive and empirically grounded work that attempts to integrate enactivist-inspired theoretical commitments with contemporary analytical approaches to large-scale brain network organisation.

# 2 Theory

*Every quality is an event; every event a quality. Every quality of event is a relation between the subject A, and the object not-A — the rest of the Universe. [...] Development does not take place in time and space. Development, becoming, and change, secrete time and space.*

—Caudwell 1938

In academic publishing, empirical papers have largely done away with a dedicated theory section (Moskovitz et al. 2024). IMRaD (Introduction, Methods, Results, and Discussion), while with some variations, became the dominant structure. If it is present, theory gets condensed into the introduction or background assumptions that guide experimental design, often remaining implicit. For a good part of empirical research with an aim to report a result, it is a justified step. Cognitive science, given its interdisciplinary nature, is somewhat of a special case: it is a scientific field in which the object of study is defined simultaneously as it is being investigated. To some extent, this is true of all sciences, but the level of agreement among biologists on what constitutes a cell is not matched by a consensus on what constitutes cognition among those claiming to study it. Theory here provides a means to carve out temporarily stable conceptual space in which empirical claims are made intelligible and negotiated beyond their statistical significance.

## 2.1 Man Made of Meat (and Words)

From an enactivist perspective, cognition is *doing*, an act by which meaning is enacted. The popularisation of the term "enaction" is accredited to Varela, Thompson, and Rosch's seminal work *The Embodied Mind*, published in 1991, but the enactive turn more broadly can be traced back to the works of Maurice Merleau-Ponty, Friedrich Nietzsche, Martin Heidegger, Spinoza, Hans Jonas, John Dewey and many others. Contemporary enactivism is a heterogeneous field of scholarship marked by substantial internal divergences (Ward et al. 2017). Perhaps the most debated distinction is that between so-called conservative and radical enactivism[1] (Hutto 2005): while "conservative" enactivism preserves a possible role for representational content reformulated in embodied terms, "rad-

[1] *Conservative enactivism* is associated with authors such as Evan Thompson, Alva Noë, and, in some interpretations, Francisco Varela. *Radical enactivism*, by contrast, is most prominently associated with Daniel D. Hutto and Erik Myin. These classifications remain contested, and many enactivists, like Ezequiel Di Paolo and Shaun Gallagher, do not fit neatly within either category.

ical" enactivism rejects representational explanations entirely[2].

This debate exceeds the scope of the present paper; thus, when I write of enactivist take, I write of it broadly, as an amalgamation of ideas anchored by the postulation that cognition is an embodied activity performed by the living systems.

[2] The schism can also be framed as that between *autopoietic* versus *sensorimotor* enactivism. For an integrative perspective, see (Kroner 2026).

**A Note on the Term "Representation"**

The term "representation" continues to function as a provisional explanatory tool in a broad range of theoretical and empirical literature referenced in this paper. The enactivist stance is often presented as a challenge to the representational view of cognition, offering a shift away from the notion that cognition entails input-output processing through internal manipulation of symbolic representations. Nonetheless, even enactivism-adjacent thinkers such as Mark Rowlands, Michael Wheeler, and Andy Clark have argued that actions may require what has been termed "minimal representation": a lean, task-specific, and task-oriented structure rather than a full internal depiction of the world (Gallagher 2008).

However, representation can be apprehended as a concept empty of explanation. As argued by Gallagher (2017, p. 106), the term can be treated as "an awkward placeholder for an explanation that still needs to be given in dynamical terms of an embodied, environmentally embedded, and enactive model". Accordingly, throughout most of this paper, I refrain from using the term. When I do employ it, I do it with caution, and in each instance I explicate what is meant by the term in that particular context.

One further note: enactivist debate on whether the process of cognition requires *representations* should be separated from the questions of whether the activity in question is *representational*. In the words of Di Paolo, Buhrmann et al. (2017): "The evidence of representational capacities in the human mind (imagination, symbolic thinking, mental imagery, etc.) is precisely that, evidence of something humans are capable of doing, evidence of a type of activity, not in itself evidence that the processes underlying this activity are themselves representational". To reiterate, representational activities do not directly entail that they are processed using representations; language can be written about as a representational structure without falling into a representational view of cognition. These are two separate discussions.

The mind-life continuity thesis, positing cognition as the process of life, sits at the core of the enactive argument. Cognition is inseparable from the autopoietic *activity* of living beings. Autopoietic here denotes how living systems self-produce, organise, and maintain themselves. "The autopoietic organization is defined as a unity by a network of productions of components that (i) participate recursively in the same network of productions as a unit in the space in which the components exist" (Maturana and F. J. Varela 2008). Living systems are thus defined as autopoietic systems, in which interactions among their parts constitute the system's ongoing existence. As these are not conceptual but living systems, they are embedded in the environment, which is in the interaction with the agent, forming reciprocally shaping relations. To preserve their autonomy, autopoietic systems require constant purposeful and adaptive interactions with their environment. As a result, any autopoietic system is inherently ascribed the faculty of cognition.

The latter reasoning has its critics, particularly pertaining to the scaling problem. Radical enactivists Daniel D. Hutto and Erik Myin (Hutto and Myin 2013) argue that autopoiesis, while necessary for life, alone is insufficient for cognition, and thus the latter should not be collapsed into biological organisation. On a similar line of argument, Keijzer (2015) explicates that if all self-producing living systems are to be taken as cognitive, the notion of cognition loses its discriminatory power.

Enactivism is not a finished theory. What follows is an *enactivist-inspired* approach, an eclectic engagement and appropriation of the existing enactivist and non-enactivist work. Rather than committing to a particular school of thought, I draw from different thinkers, notably from the work of Francisco Varela, Ezequiel A. Di Paolo and Giovanna Colombetti, whose concepts I adapt with reasonable liberty. In short, I take enactivism as one expression of nonreductive naturalism that takes brain-body-environment relations as the locus of cognition. To bring my enactivist argument forth, I first outline the foundational concepts that guide the discussion: sense-making, normativity, and the notions of autonomy and adaptivity that underlie it.

### 2.1.1 *Foundational Concepts: Autonomy, Adaptivity, Normativity, and Sense-making*

Cognition presupposes the existence of a system. Latter's self-constitution is grounded in the concept of **autonomy**. In this sense, a system is considered autonomous only if at least some of its constitutive elements are also generated and maintained by the system itself (Di Paolo, Cuffari et al. 2018). The canonical example is the cell, whose internal processes, including metabolism, protein synthesis, cellular respiration, etc., are part of the cell as well as its enabling factors ensuring the cell's continuous existence. Autonomy thus can be conceived as a generalisation of the concept of autopoiesis — an autonomous system conceived as a closed network of enabling relations (DiPaolo.etal2018). Autonomy can emerge at different levels of organization. Cell remains an autonomous system even if it is a part of a nervous system embedded in an organism, which is always in relation to its ecosystem; autonomous organisation is preserved simultaneously by differentiating levels of enabling relations. What these relations are will depend upon the dimension considered.

An organism is not a static *thing*. It is an ongoing achievement, and its autonomy is not guaranteed. The norms of viability are inherently precarious. The organism must maintain itself in relation to the environment, whose conditions are constantly shifting. The preservation of autonomy thus requires ongoing sensitivity to change — in the relation to the environment and to the self. **Adaptivity** is thus presented as a complementary concept to autonomy: it describes a form of self-relating through changes in an organism and its relations to the environment that ensure ongoing preservation of autonomy despite this precariousness.

> Adaptivity is a form of self-relating: what occurs within the organism and in its relations to the environment and other organisms is conditioned by how well or how badly its self-individuation is operating. In this sense, adaptivity works on the virtual[3] field that surrounds the current configuration of the organism-environment system (Di Paolo, Cuffari et al. 2018, p. 33).

[3] Virtual here denotes something that is real but not actualised, a space of possibilities open from the organism's current position.

Put simply, the capacity to adapt, to learn, to change, and to respond to the changing norms becomes a necessity that ensures the preservation of autonomy and its norms of viability [4].

[4] What lines of action are available depend on the organism's current state and affordances present in the environment.

Finally, **sense-making** describes how living organisms relate to their world in terms of meaning (Di Paolo, Buhrmann et al. 2017, p. 7). "The standard description of sense-making entails the co-emergence of an agent's self and a meaningful world, as well as the emergence of a normativity that guides the behavior of the coupled agent-environment system" (Sepúlveda-Pedro 2024, p. 17). Sense-making is what transforms a physicochemical environment into a meaningful world (Thompson 2007). F. J. Varela et al. (1991) called this type of transformation *a surplus of significance in the environment*. Sepúlveda-Pedro (2024) proposes to revise the classical conception where it is not just a surplus of meaning; rather, something new is being developed, not just added.

Any development or transformation, however, must preserve the core organisational closure that enables the organism to enter into meaningful relations at all. It is is precisely this imperative to preserve organisation that grounds normativity. **Normativity** is thus a closely related but distinct concept to sense-making. If sense-making brings forth a world that *matters*, normativity specifies *how it matters*. It treats the evaluative dimension of significance: the fact that environmental states are not merely registered but assessed in terms of how they promote or threaten the organism's viability. By virtue of a need to preserve one's autonomy, autopoietic systems have a tendency towards normativity.

For humans embedded in social and linguistic networks, this basic biological normativity is renegotiated. Sense-making is a process that happens at different levels of interactions, including biological, sensorimotor, intracorporeal, and linguistic (Di Paolo, Buhrmann et al. 2017). These levels are not discrete or hierarchical but mutually constitutive, each shaping and being shaped by the others[5]. Norms emerging from networked individuation extend beyond the boundaries of the organic body, creating space for concerns that often surpass and at times actively contravene its norms of viability. Celibacy, asceticism, and diet culture are just a few examples of how the body can be subordinated or even sacrificed for ideas, desires, or beliefs—ends that transcend the organic body.

[5] It must be noted that such an entanglement presents a genuine challenge for empirical investigation, as levels at which processes are measured rarely neatly map onto the levels at which they are enacted.

With its cultural and linguistic dimensions, human cognition can be seen as a highly complex and enriched version of sense-making, which, while still grounded in the same principles of autonomy and adaptivity, has expanded them to the new fields of relevance. We never stopped being bodies, men made of meat. Biological principles still govern us and how we relate to the world. Cold still feels cold and pain continues to hurt. Yet, we also choose to endure those because of moral principles, and it might even makes us feel good. We still cognize with our bodies, but in a culture and language mediated environment, they became more than their biological substrate.

**Definition 2.1.1 – Enactivist Foundational Concepts**

**Autonomy** (*structural*): system's self-sustaining, operationally closed organisation maintained through coupling with its environment.

**Adaptivity** (*dynamic*): changes in an organism and its relations to the environment that ensure ongoing preservation of autonomy.

**Sense-making** (*relational*): process through which organisms bring forth significance and value to their world.

**Normativity** (*evaluative*): evaluation of environmental states as sustaining or threatening the organism's viability.

## 2.2 *Enactment Constrained*

The enactivist perspective is developmental, positing an individual who brings forth a world and self across time. "Bodies are extended in time, involve processes at multiple spatial and temporal scales, are open and have undefined boundaries" (Di Paolo, Cuffari et al. 2018, p. 113). Any experiment, by necessity, is constrained to an isolated object of the study, a dimensionally narrow slice of the ongoing relational process. There is an inherent temporal gap between the conception of an extended body and a time-constrained experiment. In the 90s, F. Varela (1996) put forward neurophenomenology as a new research program with an aim to push science that bridges third-person data with first-person experience. Whether directly referring to neurophenomenology or not, the enactivist project shares its working hypothesis that "phenomenological accounts of the structure of experience and their counterparts in cognitive science relate to each other through reciprocal constraints" (ibid., p. 342). Reciprocal constraints here refer to a research principle that takes subjective reports and 'objective' neuroscientific measurements as equally valid and mutually constraining sources on which theories of the mind are to be built. It can also be understood as a broader research program, calling for methods and theories to inform and be informed by one another across levels of analysis.

In the previous paragraphs, I introduced four grounding enactivist concepts: autonomy, adaptivity, normativity, and sense-making. These are formal definitions. The goal of the empirical is applying them to *the concrete*—a specific enactment under specific conditions. In the case of this study—a lab-based experiment.

The exact experimental conditions of the study are described in the Methods chapter. For the purposes of this discussion, it suffices to note that we employed functional magnetic resonance imaging (fMRI) to capture participants' brain activity while they were exposed to textual climate-related statements, categorised by us as neutral, threat-, or solution-oriented. In other words, people were reading while lying down in a noisy scanner, having been told to move as little as possible. Evidently nothing close to how news is read by most people, not even how they appear in our feeds. The ecological validity of reading is lacking. What is captured is the activity[6] of understanding[7].

[6] In everything that we do, no matter how much we sweat and how many and which of our muscles contract, in enactivist terms, we are always to be found in an act. While tautological as an idea, activity is the condition of being alive as a situated body (Di Paolo 2023).

[7] A critical assumption when approaching neural dynamics from enactive-inspired philosophy is that those patterns are of the process and not the measurement. Current state-of-the-art network neuroscience methods for neuroimaging data, in order to remain interpretable, typically require the imposition of discrete structure, be it in time (state segmentation) or in space (parcellation). Such discretisations inevitably obscure fine-grained details of neural dynamics, leaving researchers with abstracted patterns of the underlying emergent processes. The interpretative task, therefore, is to treat these patterns as partial access points to the process itself, remaining attentive to the methods and measures through which they are produced.

Eye movements are an undeniable component of the reading process. However, to treat them as the primary locus of relevance from an enactivist perspective constitutes a superficial interpretation of the tenets of the theory. At its core, reading is a cognitive engagement with the text, something akin to thinking rather than following a line of visual patterns. For the purposes of this analysis, I will be using two terms. I will employ *reading* to refer to the entire act, including the mechanical process of eye movements and covert visual attention, and *understanding* as the concurrent meaning-making that could be done with the same statements in different modalities. Sense-making encompasses both. These are not to be understood as separate events or engagements. Sensory input changes depending on how one moves[8]. If a text is written in a language the reader is familiar with, reading is understanding, even in the case where what is meant by a certain sentence remains elusive[9]. The distinction between *reading* and *understanding* is made for the clarity of the developed line of argument in reference to the treatment of an empirical observation and statistical comparison of obtained data.

[8] In enactivist terms, this is referred to as *sensorimotor contingencies*, the regularities in how sensory input changes as a function of movement.

[9] One can think of how reading is used in sentences like "what is your reading of the text?", which capture both conditions of text being read and interpreted.

Language is also not an exception to the processes of relational constitution; according to (Di Paolo, Cuffari et al. 2018, p. 107): "Language has no abstract, self-standing theoretical centre, but is instead a concrete open totality embedded in networks of material, biological, and sociocultural codetermining relations". In other words, language comes from the totality of human Umwelt[10]. "In fact, language is first responsible for enhancing a relation of participation in the world, and of speaking to the world, and listening to it" (Di Paolo 2023, p. 16). From a cognitive linguistic perspective, such mapping of imagined structure onto perceived structure has been termed *conceptual blend* (Fauconnier and Turner 2008). From an enactivist view, the conceptual blend is an ongoing enactment; there is no prior to be mapped on. Given that language restructures how we enact a meaningful world, there are no concepts that are not blends of lived experience and its linguistic mediation.

[10] One of the best metaphors evoked to capture this view of language is that of a ball made out of rubber bands, something fundamentally entangled (ibid.).

> In other words, the socially concretised object exists in its relations of form, kind, number, measure, value, etc. — relations, in other words, of ideality. These relations do not reside in the minds or brains of individuals (this would imply some kind of naive materialism) but in the ongoing circulation between practices, world, and linguistic bodies (Di Paolo, Cuffari et al. 2018, p. 207).

Ideality here is a term adopted from Ilyenkov's philosophy and has nothing to do with the imagined, ideal or perfect form (Ilyenkov 2012). Ideality is how socially embedded practises make something real without reducing it to any single material instance by constructing virtuality. It denotes the existence as patterns of form, kind, number, measure, value etc. In other words, ideality is a property of relations, not things. For example, one can think of the value of money, the meaning of a word, or in our case the significance of *Climate Change*.

There are climate changes occurring due to human industrial activity that are measurable, physical changes. And then there is *Climate Change* : a culturally enacted practice, brought forth through language, media, political discourse, action taken and restrained from. From a philosophical perspective, what changes is the intentionality. The concept of Climate Change is a shared reference to shared enactments of meanings. First, it is an indication of immediate disturbance in the environment. Second, the discourse around it, generates its own discursive forms that are recursively reused to enact further meanings. Climate Change, in this case, is a socially concretised object, brought forth through the actions that engage with it. Action in relation to Climate Change extends to stance taking—the cognitive-affective orientation that emerges through repeated engagement with climate information. Cognitive-affective positioning toward a socially concretised object is also the orientation leading neural data analysis and interpretation.

### 2.2.1 *Affective is Cognitive*

Enactive cognition, according to Colombetti (2014), is intrinsically affective cognition. If Descartes split the world into two fundamental substances: *res cogitans* (thinking substance, mind) and *res extensa* (extended substance, matter/body), Colombetti brings them back together in one feeling minded body[11]. If we argue from an enactivist worldview, she posits, cognition and emotion are to be understood as one and the same process:

> Rather, both cognition and emotion turn out to be instances of the relentless sense-making activity of the precarious living organism as it maintains itself via continuous processes of self-regulation and exchange with the environment. (Colombetti 2014, p. xvii)

Affectivity here is defined by the lack of indifference to the world: "a sensibility or interest for one's existence" (ibid., p. 1). A mood is not something that comes from *within* or *without* but is a type of being in a world itself; it is a particular mode of care. Care is what minded bodies do to sustain their autonomy and ensure continuous existence under precarious conditions that always threaten to undermine their norms of viability. It is normativity in action. Affective experience is not merely carried by the body but is constituted by its concrete materiality; thus, the ascription of the adjective "wet" to cognition that involves homeodynamic processes of self-regulation. Wet cognition goes beyond thinking about why we are feeling anger; it is anger itself: shifts in the increase of the heart rate, vasoconstriction and vasodilation, increased respiration, digestive suppression, musculoskeletal tension, etc. Physiological state is an affective state and, at the same time, a cognitive state. They encompass the sense-making of the world.

In this sense, human affectivity can still be understood in terms of primordial affectivity that characterises all sense-making organisms but enriched through the expansion of Umwelt as we participate in a linguistically enhanced world. In a way, we could say that "linguistic agency has the power of thematizing the body, and for this reason, of displacing itself from it" (Di Paolo, Cuffari et al. 2018, p. 196). We are not the only species to have a cascade of the aforementioned physiological responses associated with stress or fear (Panksepp 1998), but humans are, arguably, the only ones to recognise and describe those states as "anxiety about the state of world affairs".

From the perspective of socially embedded language practice, sense-making involves cutting across historical and ecological dimensions. De Haan (2017) more broadly characterises sense-making as a contingent and temporal process with a system extended over time. Whenever an agent is considered in coupling with

[11] As noted by Kroner (2026) "Ironically, this predicament is not entirely lost on Descartes himself. In the sixth (and very last) of his Meditations (1641) he writes: "Nature also teaches me, by these sensations of pain, hunger, thirst and so on, that I am not merely present in my body as a sailor is present in a ship, but that I am very closely joined and, as it were, intermingled with it, so that I and the body form a unit" (AT VII 81; CSM II 56)."

the environment, what matters for sense-making is the entire accumulated history and ongoing dynamics of the agent and the environment (Di Paolo, Buhrmann et al. 2017). Viewed from that perspective: "There is no explanatory constraint from the enactive perspective to reduce the determinants of sense-making to anything less than the history-dependent coupled system as a whole" (ibid., p. 226). But there is a problem applying that idea to an experimental design and, even further, to a quantifiable variable. However, as argued by Lee (2023), taking enactivist stance does not mean that every explanation has to be at the level of agent-environment coupling, only that there is a need to situate properties within that context. In his words:

> Not all explanations must target the appropriate unit in its totality. For example, if cognition must be understood in terms of the bodily activities of organisms coupled with their environments, it does not follow that neuroscience cannot study the signalling properties of neurons, only that understanding cognition fully requires situating those properties within the embodied and embedded agent. (ibid., p.161)

Lee here echoes the proposal by Meyer and Brancazio (2022) to treat enactivism as a *philosophy of nature*. If a paradigm seeks to operationalise, to provide unifying methodologies, programs, and tools for investigating and selecting questions to be investigated empirically, philosophy of nature is an attempt to bring all together into a coherent holistic *worldview*.

### 2.2.2 *The Data*

The fMRI, like any other imaging modality, produces data—structures of numerical values that require tools capable of interpreting them and inferring desired information about the process of interest. Network neuroscience developed on the basis of the availability of tools providing such access. Enactivism, on the other hand, is a holistic theory, and "it is difficult to operationalise holism. Neither experimental control nor the division of labour in science allows for all factors to be taken into consideration at once" (Gallagher 2017, p. 21). Operationalisation is difficult. Nonetheless, given the experiment setting, enactivist theory offers a ground to build a less isolated interpretation of the neural data as it relates to the cognitive-affective processes during engagement with climate-related texts.

## 2.3 *Networks in Action*

Operationalising enactivism immediatelly leads to the analysis of agent-environment interaction *instances*. Network science is a science of relationships, capturing "the pattern of interactions between the parts of a system" (Newman 2018). For much of its history, neuroscience was concerned with parts and their functions. Network science provides an alternative set of theoretical, computational, and empirical tools that are used to study complex systems through mathematical representations (Medaglia et al. 2015). As these tools were being developed and spread across disciplines, the way was paved for the brain to be examined as a complex dynamical system characterised by distributed interactions (Barabási et al. 2023; Medaglia et al. 2015).

At their core, brain networks are abstract models of structural or functional neuron-to-neuron or region-to-region relationships. Unlike the approaches that reduce neural interactions to pairwise comparisons, such as bivariate correlation or seed-based connectivity analyses, network-based representations[12] provide an advantage by enabling quantitative analysis of heterogeneous interactions within a unified mathematical framework (Medaglia et al. 2015). Moreover, they aid the investigation of higher-order, multivariate patterns, revealing emerging organisational features of brain activity that remain invisible in pairwise analyses.

[12] It is important to note that the term "representation" in network science refers to the method of investigation rather than to the intrinsic properties or functioning of the system. A network here refers to a *mathematical representation* of a real-world complex system (Rubinov and Sporns 2010). Network represents the system but does not imply that the system itself is inherently representational.

The formal foundation of network analysis is provided by graph theory. Graphs, technically, are grounded in pairwise relations, but their tools scale to capture the higher-order structures described above. In graph theory terms, networks consist of *nodes* that are standing in for neural units and *edges*—structural or functional connections between them (Sporns 2018). The simplest graph form is an *adjacency matrix,* where each cell shows the presence or absence of an edge between two nodes or their weight—strength of the link. Graph measures enable the quantification of matrix properties and their comparison across scales and domains (Iñiguez et al. 2020; Sporns 2018).

Global graph measures, such as the measured *global efficiency*, *clustering*, and *modularity*, capture dynamics *of* networks (Bassett and Sporns 2017). They are static structural measures; they do not capture dynamics happening *on* networks. The distinction here is important. Dynamics *on* networks refers to how nodal activity evolves as a function of time, whereas dynamics *of* networks refers to changes in the edges themselves, whether in their presence or their weight. While measures of networks can be used to infer or predict dynamics on networks, for example, global efficiency could be used as an approximation for neuron firing, what is being measured and reported are structural properties that *constrain* or *shape* dynamics. Functional network graphs, in particular, present a curious case where graph measures capture the structure inferred from an underlying dynamical process.

Grasping the anatomical structure of the brain using graph theory is relatively intuitive. Given the chosen method, there is or there is not a node (neuron or brain region) and an edge (white-tracts or synapses quantified) connecting it to the other node. As stated by Barabási et al. (2023) structural connectivity refers to "ground truth," while functional connectivity estimates statistical associations among neural time series. Structure-function coupling in the brain remains an active area of investigation (Suárez et al. 2020). However, it is not controversial to claim that function cannot be directly derived from anatomical and morphological structure alone, rendering functional connectivity an enduring focal point in brain network research (Mamat et al. 2024; Yan et al. 2022).

Functional brain networks are relational, dynamic patterns of neural coordination (Rubinov and Sporns 2010), defined by statistical associations among neural time series rather than a web of physical links that propagate neural signals (Sporns 2018). Precisely because functional networks are derived from statistical co-fluctuations of aggregated neural activity, they are considerably more ambiguous to interpret than their structural counterparts (Duff et al. 2018; Z. Wang et al. 2021). Characterising functional connectivity therefore requires its own conceptual vocabulary.

### 2.3.1 *Never at Rest*

In 1995, Biswal et al. (1995) were among the first to show that distant brain regions exhibit correlated activity even at rest. Using BOLD imaging, they identified coherent fluctuations across the motor network in the absence of any task engagement. Today, resting state networks (RSNs), such as default mode, sensorimotor, salience, and executive control networks, are considered to capture intrinsic functional organisation—spontaneous and coherent fluctuations that maintain synchronised activity in the absence of explicit cognitive demands (Suárez et al. 2020). Numerous comparative studies have demonstrated that patterns of resting-state connectivity can predict clinical phenotypes and behaviour (Vaidya and Gordon 2013), age (Kardan et al. 2022) and can even be used as neural fingerprints to identify individuals across scanning sessions (Finn et al. 2015). Given that resting-state research marks the origin of functional network conceptualisation, its enduring dominance in graph-theoretic studies is not surprising (Farahani et al. 2019).

Resting state studies illustrate that there is no blank state upon which tasks can be imposed. An ngagement with a changing environment is always an adaptation of a preceding brain state (Deco et al. 2011). In other words, task-evoked activity is not composed of isolated discrete computations but reflects ongoing self-organisation constrained by intrinsic network architecture (Cole et al. 2014; Hearne et al. 2017).

Graph measures such as density, modularity, clustering coefficient, global efficiency, and betweenness centrality provide a means to trace and quantify evolving patterns of network organisation over time (Hassett et al. 2024). These measures are descriptive abstractions, and while relatively simple, this simplicity also contributes to their generalizability (Fornito et al. 2016). However, because they rely on aggregate topological summaries, they also often obscure the richness of time-varying brain states. In particular, aggregate graph measures are largely insensitive to the temporal ordering and transition dynamics, limiting their capacity to capture less stable patterns, motivating complementary dynamic connectivity approaches.

Dynamic approaches such as sliding-window correlations, hidden Markov models, and co-activation pattern analyses capture time-resolved fluctuations in brain activity and connectivity, revealing transient and recurring states of network organisation (Hutchison et al. 2013). Among these, co-activation pattern (CAP) analysis is distinguished by identifying recurring whole-brain activity configurations at the level of individual time points (Liu and Duyn 2013), thereby offering a temporally fine-grained perspective that complements graph-theoretical summaries of network structure.

### 2.3.2 *The Times are Changing*

The last few decades have accumulated increasing support for the claim that transitions between brain states are not random[13] (Allen et al. 2014; Deco et al. 2011). Further evidence points towards those states being hierarchically organised in time, suggesting that transitions between them are not purely stochastic (Vidaurre et al. 2017). Instead, the brain appears to cycle preferentially among

[13] As reported by Vidaurre et al. (2017), non-random transitions have also been found across alternative state-space formulations, including electroencephalographic microstates, metastable attractor dynamics, and energy landscape models defined by local minima.

a limited set of meta-states, each with distinct spatial features. These findings regarding temporal organisation bring us back to enactivist accounts of cognition as an ongoing, history-dependent process, where neural trajectories parallel paths in sensorimotor space. That is, the non-randomness of empirically defined states aligns with the enactivist view that agent-environment coupling is continuous and shaped by the system's prior states.

Even in the early days of enactivist theorising, Maturana and Varela placed strong emphasis on the nervous system as a system embedded in but partially decoupled from generic biological autopoietic processes:

> Operationally, the nervous system is a closed network of interacting neurons such that a change of activity in a neuron always leads to a change of activity in other neurons, either directly through synaptic action, or indirectly through the participation of some physical or chemical intervening element. Therefore, the organisation of the nervous system as a finite neuronal network is defined by relations of closeness in the neuronal interactions generated in the network. (Maturana and F. J. Varela 2008, p. 127)

Barandiaran (2017) contends that such an argument falls into solipsism by failing to properly account for the constitutive role of sensorimotor dynamics. In other words, he claims that it reduces the life of the mind to biological autonomy. While critical of the biology-oriented formulation of autonomy in the early work of Varela and Maturana, Barandiaran defends the autonomy of mental life by redefining it in sensorimotor terms.

> Mental life's specificity lies in the fact that the environment is not simply a source of perturbations (or a source of energy and matter) for an otherwise operationally closed network. On the contrary, the nervous system's activity achieves its closure, its large scale coherence, through embodied interaction: i.e. through fine grained coordinations between neurodynamic and sensorimotor correlations. (ibid., p.419)

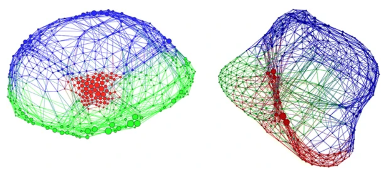


Figure 2.1: Transition diagrams of oscillatory states for a 3-oscillator network controlling a robot switching between two light sources. Red nodes: uncommitted states; blue/green nodes: commitment to the respective light source. Left: freely behaving agent. Right: passively-coupled agent with identical input. Reprinted from unpublished results of Aguilera et al. (2015) as cited in Barandiaran (2017), available under Creative Commons BY-SA at http://maguilera.net.

He further illustrates the emergence of sensorimotor autonomy through the situated HKB two-robot model.

In this model, whether sensory input is derived from behaviour or fed directly into the system determines the resulting density distribution of the effective phase space. "Thus, what matters is not the sensory input, but the fine grained temporal structure of sensorimotor contingencies as they are enacted by the agent. To say it differently, even if one considers that mental states supervene on brain processes, there is a sense in which sensorimotor dynamics are constitutive" (ibid., p. 420).

Taken together, if the organisation of prior brain states constrains subsequent ones, the brain is, in this sense, self-referential. Simultaneously, both the system and its current state are constituted through ongoing interaction with the environment. Neurodynamics may thus be considered and studied as an operationally closed system, but this closure should not be misconstrued as isolation. As F. J. Varela (1992) emphasised in his later work, "operational" is meant to capture closure in the mathematical sense of recursivity, not in isolation from the interaction with one's environment.

### 2.3.3 *Pessoa's Network Model of Emotion*

This balance between self-referential brain states and their constitution through engagement with the environment is reflected in Pessoa (2017) network model of emotion. Pessoa argues for the case that "emotion is a large-scale network property of brain function" (ibid., p. 369), mobilising both the body and the brain. Subsequently, emotions are best described in terms of coordination dynamics rather than a modulatory bias on otherwise cognitive systems (Pessoa 2018). Although Pessoa does not directly cite the work of Colombetti, his words echo those of her proposal that emotions, or better *emotional episodes*, are best conceptualised as dynamical patterns, namely, as self-organising configurations of the organism or "emotion forms" (Colombetti 2014, p. 82)[14].

[14] As she further notes: "These patterns are flexible and loosely assembled, can be culture specific and even individual specific, but may also recur reliably across cultures."

The centrepiece of neurobiologically grounded empirical model of affective cognition, in the work of Pessoa (2017) is a functionally integrated system of large-scale cortical–subcortical loops.

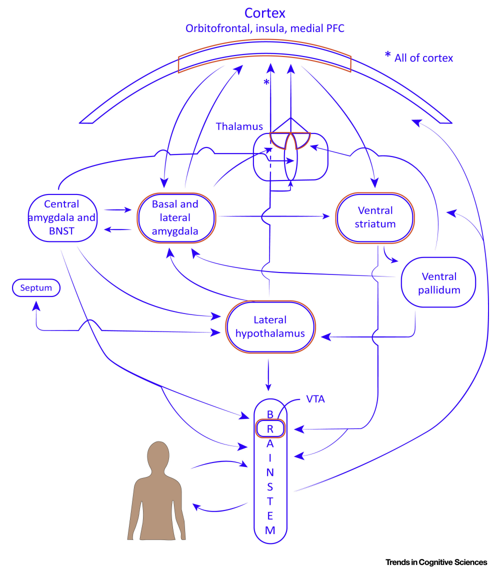



Figure 2.2: Functionally integrated systems of large-scale cortical–subcortical loops. Taken from Pessoa (2017).

The cortex–amygdala system is a primary example: the basolateral amygdala connects extensively with the cortex, the hypothalamus, and the brainstem, while the extended amygdala propagates signals across the entire neuroaxis. Yet even as a system, it is not an isolated one; it interfaces with others, particularly the ventral striatum and septum–hippocampus systems. For Pessoa, emotion does not reside in one region or even a network; it emerges from their coordination dynamics. If networks are functionally overlapping, brain 'signatures' of emotion are highly context-dependent and unlikely to map neatly onto fixed resting-state networks or generalise across tasks and conditions.

## 2.4 *Framing Frames*

As argued so far, agents in the enactive approach are autonomous, adaptive, world-involving networks of processes, establishing constitution as the default mode of engagement. However, as Di Paolo (2023) states, dynamics of engagements tend to settle into metastable conditions, "simplifying a situation of constitution into one of transaction or one of interaction and making the dynamical systems approach directly applicable" (ibid., p. 169). He explicates that in an ontological sense, constitution entails creation of new possibilities, transaction—restructuring of the landscape of potentialities, and interaction—actualisation of existing potentialities. In other terms, interaction changes dynamics, transaction structures, and constitution organisations.

| Engagement | What changes | Production (ontic) | Production (ontological) |
|---|---|---|---|
| Interaction | dynamics | dynamical invariants, grip, properties | concretized potentialities |
| Transaction | structures | habitus, learning, settings, styles | reconfiguration of potentialities |
| Constitution | organizations | bodies, niches | concretized possibilities |

Figure 2.3: Modes of engagement. Taken from Di Paolo (2023)

Most available methods for studying cognition, due to methodological constraints, are limited to capturing interactional or transactional changes. Cognitive network neuroscience, in particular, operates primarily at the level of interactions. This reflects both the level of abstraction at which neural organisation is observed and the focus on the neurodynamics. Adequate tools to account for how these dynamics are constituted through ongoing sensorimotor engagement and sense-making, however, are still lacking. As it stands, constitution remains an ongoing process, but one that unfolds at spatial and temporal scales that exceed those accessible within typical experimental designs.

From an enactive standpoint, language is not an abstract code mapped onto mental representations but an ongoing activity constituted through cultural and social engagement (Di Paolo, Cuffari et al. 2018; Rodríguez Jordá and Di Paolo 2025). As stated above, language is inevitably intertwined with other cognitive domains. This, in turn, allows us to hypothesize and approach understanding of the text as an interaction that can be measured through changes in large-scale brain dynamics. "Frame" in this case emerges as a particularly useful theoretical notation that helps to delineate what is captured while measuring brain dynamics during reading if emphasis is to be drawn on the understanding of the text.

Frames[15], by the often cited definition by Entman (1993, p 52): "promote a particular problem definition, causal interpretation, moral evaluation, and/or treatment recommendation for the item described". While initially mainly applied to gain/loss and risk assessment during decision-making contexts, in recent years the framing theory has been adopted more widely to investigate "when, how, and why different forms of language — including differences in word choice, grammar, concreteness, and emphasis — affect how people respond to a message" (Flusberg, Holmes et al. 2024, p. 106). Framing is an unavoidable feature of human communication. Frames are formed by their socio-historical context and can be called to *frame* the interaction onto a specifc surface of context. To be expressed, a message has to be given a form to be carried out. A frame is simply a more deliberate and recognizable instance of that inevitable shaping.

[15] Frame evokes a sense of rigid shape, but this is not what is argued for by bringing framing theory into the discussion. Personally, I find *flavour* or *colouring* more intuitive alternatives to indicate the looseness and felt aspect of the type of quality "framing" achieves. In general, the concept of frame remains vague. Despite the arguments against, the terminology of framing is adopted to ground the current argument in broader debates regarding language and communication.

Frame is a quality of the whole, a gross measure. While comprised of fine-grained components, the frame emerges as a systems-level property. For the sake of clarity, it is important to note that, depending on the level they are operating at, frames can be categorised as cognitive, semantic, or communicative (Flusberg, Holmes et al. 2024). Communicative frames primarily describe how the message is being communicated, its form and content; cognitive frames capture within what context a person interprets the message she is exposed to; while semantic frames refer to cognitive frames evoked by language.

Given the co-constitutive nature of communication argued by the enactivist stance, the actualized[16] frame is always an interaction term between all aforementioned frames: the outcome of the dynamic interplay between linguistic structure, individual histories, and situational context. This resonates with Derrida's claim that language has no fixed centre, that there is no single signified meaning (Derrida 2001). To use his terms, language exists as *différance*: a process of difference and deferral, whose meaning is endlessly delayed. While Derrida articulated *différance* as a relationship between signs and other signs, the insight can be extended to the embeddedness of signs in cultural and social environments in which an agent enacts those relations. When it comes to languaging, enactment is one, but authors are many. Following, understanding on a level of framing is not the application of a pre-existing cognitive frame to that of a message, but the situated enactment of meaning at the intersection of cognitive, semantic, and communicative dynamics. Neurodynamics, when tracked over the course of an event, affords access to the ripples of this interaction.

[16] *Actual* captures that which is presently realised.

## 2.5 *Chapter Summary*

This chapter began with an outline of the foundational tenets of the enactivist theory of cognition. Cognition was presented as a twofold enactment of the world and the mind, and the core enactivist concepts of autonomy, adaptivity, and sense-making were shown to allow tracing of cognition from the basic processes of life to its more complex expressions within culturally and socially structured webs of meaning. Drawing on work by Di Paolo, Cuffari et al. (2018), it was argued that the introduction of the latter dimensions has fundamentally changed human cognition by expanding the field of relevance to the field of ideality, underlain by a new type of normativity. This expansion, however, has for the most part been left out of empirical investigation. Given that the fMRI data for the present study comes from an experiment in which people were exposed to climate-related statements, the act of interest was taken to be the understanding of the said texts. Climate Change was argued to be a socially concretised object, and the affective stances people take toward it were taken to be ways of enacting it. Having done away with locating cognition within the boundaries of the brain, affect, following Colombetti (2014), was considered an integrated aspect of cognition. The cognitive-affective state was presented as something that can be considered (even if only partially) accessible through probing brain network dynamics.

Graph theory and co-activation pattern analysis (CAPs) were introduced as two complementary network science methods that grant possibility to study brain as a dynamical autonomous, adaptive system. The large-scale brain network configuration patterns were taken as the experimentally available site of the broader affective sense-making process. Neurobiologically grounded support for the integrated cognitive-affective state view was provided with an introduction to the network model of cognition developed by Pessoa (2017). Given the view of cognition as a twofold enactment, the understanding of textual information was considered to depend both on the content of the message and on the history and current state of the person reading it. Communicative frames were thus taken to be an interaction among the entire network of variables in a concrete agent-environment coupling. In view of cognition that cuts across ecological and historical dimensions, it was emphasised that current tools are not capable of capturing the full breadth of cognition theorised by enactivist philosophy. However, by conceptualising brain as a self-organised, operationally closed system, what could be observed is the ripple of the interaction in brain network adaptation during the unfolding of the cognitive event of interest.

An *enactivist-inspired* theoretical stance was aimed to be presented throughout. Overall, enactivism is treated as a philosophy of nature that integrates diverse research strands and paradigms into a more holistic account of cognition. With theoretical commitments in place, the following chapter details the methodological choices, their underlying assumptions, strengths and shortcomings.

# 3 Methods

*"All that is very well," answered Candide, "but let us cultivate our garden."*

—Voltaire 2009 (originally 1759)

## 3.1 Experiment

### 3.1.1 Participants

The study was a part of REASON (Responses to threat- and solution-oriented climate news) research project on the informational and emotional aspects of climate communication and its impact on society[1]. For the present analysis, only neuroimaging data from 32 out of 39 right-handed, German-speaking adults living in Austria were used (age: $M = 25.9$, $SD = 6.9$, range = 19–45 years; $n_{\text{female}} = 20$). Participants were recruited through the Study Participant Platform hosted by Vienna CogSciHub and through posted advertisements. Standard MRI exclusion criteria were applied, including pregnancy, claustrophobia, and neurological or psychiatric disorders. As the task required reading, uncorrected visual impairment was included as an additional exclusion criterion. Participants, who did not complete at least one full part of the experiment protocol, or who had excessive scanner motion, were excluded from the analysis, resulting in a usable sample of 39 participants. Of the retained participants, 7 were missing Part B of the task due to technical issues or early termination and were excluded in condition-level analyses. Prior to and following the scan, participants completed questionnaires assessing personal attitudes towards climate change. However, questionnaire data were not utilised in the present study.

[1] REASON project was funded by the Austrian Science Fund (FWF) [10.55776/P37293]. For more information on the project, see https://reason.uni-graz.at/en/.

### 3.1.2 Task Design

During the experiment, participants were exposed to climate-related statements framed as threat-oriented, solution-oriented, or neutral. In total, 57 statement pairs were presented across two runs (19 pairs per condition), with 29 pairs presented during the first run and 28 during the second. The statements were written specifically for this experiment by linguists and corresponded to 19 climate-related themes (Ringhofer et al. n.d.). The themes included average temperature, urban space, water and soil sealing, forest and drought, agriculture and soil, health, snow and glaciers, heat waves, biosphere and habitat, pests and beneficial insects, footprint and housing, politics and climate goals, consumption, diet and meat, electricity and energy, transport, travel, and media communication. An Example of threat-, solution-oriented and neutral statements for the heatwave theme is given in the box below. Statements were presented randomly, a shorter statement stimulus ($\approx$ 6 s) followed by a longer statement stimulus ($\approx$ 13 s). After the exposure to each statement pair, participants rated their affective states using 9-point Self-Assessment Manikin (SAM) scales for valence and arousal. Before and after the two task runs, resting-state fMRI data were acquired over 10 minutes. Participants were instructed to relax without closing their eyes and not to think about anything in particular.

**Climate statement examples for Heatwave theme**

Solution-oriented

*Since the number of "tropical days" per year—days with temperatures above 30°C—is expected to triple over the next 10 years, what used to be record-breaking temperatures are now the norm. For this reason, it makes sense to replace concrete—which absorbs heat—with temperature-regulating materials (such as wood) in buildings as much as possible.*

Threat-oriented:

*The number of days with temperatures above 30°C has risen dramatically over the past 100 years and is expected to triple in the next 10 years alone. Temperatures that used to be record highs are now the norm. By the end of the 21st century, dangerous heat waves will become a permanent feature of summer in Austria, with up to 80 "tropical days" per year.*

Neutral:

*Our weather follows various patterns that can be statistically verified. For example, there is a seven-day cycle, as weekends are the days when it rains most frequently in Austria. A very reliable annual weather phenomenon is the "Ice Saints," a cold snap in mid-May that coincides with the name days of Mamertus, Pankratius, Bonifatius, and Sophia, from whom the name derives.*

Original statements in German: *Da sich die Anzahl an „Tropentagen" im Jahr mit einer Temperatur über 30°C voraussichtlich über die kommenden 10 Jahre verdreifachen. Werte, die früher einen Rekord darstellten, bilden heute den Durchschnitt. Daher ist es sinnvoll, den Hitzefänger Beton durch temperaturregulierende Materialien bei Gebäuden (z.B. Holz) soweit wie möglich zu ersetzen. Die Anzahl der Tage mit über 30°C ist in den letzten 100 Jahren dramatisch angestiegen und soll sich bereits in den kommenden 10 Jahren sogar verdreifachen. Werte, die früher einen Rekord darstellten, bilden heute den Durchschnitt. Bis zum Ende des 21. Jahrhunderts werden gefährliche Hitzewellen in Österreich ein dauerhafter Begleiter des Sommers, mit bis zu 80 „Tropentage" pro Jahr, werden. Unser Wetter hat verschiedene Rhythmen, die sich statistisch nachweisen lassen. Zum Beispiel gibt es den Sieben-Tage-Rhythmus, denn Wochenendtage sind in Österreich die häufigsten Regentage. Eine sehr zuverlässige jährliche Wettererscheinung sind die Eisheiligen, ein Kälteeinbruch Mitte Mai an den Namenstagen Mamertus, Pankratius, Bonifatius und Sophia, woher der Name rührt.*

To validate that condition labels aligned with participant self-evaluation, linear mixed-effects models were fitted with condition as a fixed effect and participant as a random intercept. Data were screened for outliers using condition-wise $z$-scores and checked for normality using Shapiro–Wilk tests and residual diagnostics. In addition, data distributions were visualised using box plots to inspect rating differences across conditions.

## 3.2 Data

### 3.2.1 MRI Data Acquisition

Participants underwent two resting-state fMRI runs (10 min each) and two task-based fMRI runs (20 min maximum). MRI data were acquired on a Siemens

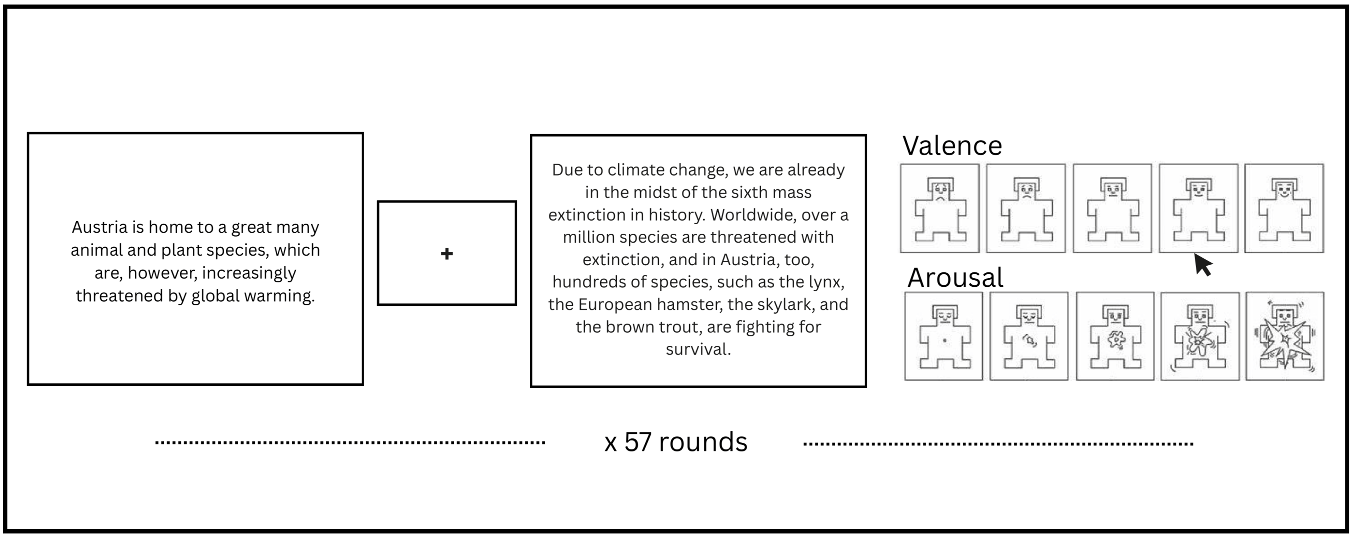



Figure 3.1: Task Design. Participants were exposed to climate statements framed as threat-oriented, solution-oriented, or neutral. Shorter statements were followed by longer statements on the same theme. SAM evaluations were collected after each statement pair. For the fMRI condition analyses, only TRs corresponding to the duration of climate statement exposure were extracted, excluding fixation and rating periods. Statement pairs were presented in random order across 57 trials during two runs. Texts in the illustration represent a threat-oriented statement pair.

Skyra 3T scanner using a 32-channel head coil. Structural data consisted of a T1-weighted MPRAGE sequence (TR = 2300 ms, TE = 2.43 ms, TI = 921 ms, flip angle = 8°, voxel size = 0.8 mm isotropic, GRAPPA acceleration factor = 2). Functional data were acquired using a multiband gradient-echo EPI sequence sensitive to BOLD contrast (TR = 1300 ms, TE = 34 ms, flip angle = 66°, number of slices = 60, in-plane resolution = 2.2 × 2.2 mm, slice thickness = 2 mm, distance factor = 20 %, multiband acceleration factor = 4, partial Fourier = 0.875, phase encoding direction = posterior-anterior). To account for potential field drift and to correct for susceptibility-induced geometric distortions at different stages of data acquisition three fieldmaps were acquired throughout the session, each consisting of a gradient-echo fieldmap and two EPI acquisitions with opposite phase-encoding directions. All fieldmaps shared the same resolution and were aligned to one another.

## 3.3 *Preprocessing*

To ensure reproducibility and transparency, data was organised in BIDS format. The first preprocessing step was performed using `fMRIPrep 25.1.3` (Esteban et al. 2019) with predefined parameters. Briefly, anatomical preprocessing included INU correction, skull-stripping, tissue segmentation, and spatial normalisation to MNI152NLin2009cAsym via nonlinear registration. Functional preprocessing included head-motion correction, distortion correction using a B0-nonuniformity map estimated from two EPI acquisitions with opposite phase-encoding directions, and co-registration to the T1w reference via boundary-based registration.

Post-processing of fMRIPrep outputs was performed using `XCP-D v0.13.0` (Mehta et al. 2024). In short, nuisance regression was conducted using a 36-parameter model, including six motion parameters, their temporal derivatives and quadratic terms, as well as global signal and its expansions. Volumes exceeding a framewise displacement threshold of 0.5 mm were censored, and the BOLD signal was subsequently bandpass filtered between 0.01 and 0.08 Hz and spatially smoothed with a 6 mm FWHM kernel. Parcels with less than 80% coverage were excluded from further analysis. All preprocessing steps were run in the Neurodesk (Renton et al. 2024) environment to ensure consistent software dependencies across systems.

Subsequently, BOLD signal was parcellated into 456 regions of interest using the XCP-D built-in 4S456 atlas ("PennLINC/AtlasPack" 2026)—Schaefer 2018 (Schaefer et al. 2018) cortical parcellation supplemented with subcortical structures. The 400 cortical parcels were derived from intrinsic functional connectivity by grouping functionally similar voxels together, and are explicitly constrained to fall within seven or seventeen large-scale, resting-state networks defined by Yeo et al. (2011). The inclusion of subcortical structures ensures whole-brain coverage. However, the BOLD signal in subcortical regions was frequently insufficient in coverage, resulting in a high number of subcortical structures falling below the 80% coverage threshold. While the use of a predefined atlas entails loss of fine-grained spatial detail and fails to account for individual differences in intrinsic functional organisation (Li et al. 2025), it ensures stability and reproducibility of results. Hence mean time series were extracted per parcel to construct functional connectivity matrices for subsequent graph-theoretic analysis.

## *3.4 Graph Analysis*

### *3.4.1 Functional Connectivity*

Functional connectivity was computed at the subject level for each condition using Pearson correlation between the mean parcel time series (concatenated across runs A and B) across all parcel pairs, yielding one matrix per condition (threat, solution, and neutral) per participant. Three condition-specific regressors were derived by convolving the experimental design with SPM's canonical HRF and normalising the resulting time series. Only timepoints exceeding a threshold of 0.8 on the normalised regressor were retained for further analysis. A cosine drift model was additionally applied to account for low-frequency signal fluctuations. Finally, Fisher-$z$ transformation was applied to all correlation matrices to normalise the distribution of correlation coefficients. The result is a functional connectivity matrix representing task-locked co-activation during the given condition.

### *3.4.2 Global Graph Measures*

Graph measures were derived using the open source Python package `NetworkX` (Hagberg et al. 2008), tailored to the study of complex networks. Prior to obtaining graph measures, functional connectivity matrices were binarised at a threshold of 0.1, retaining only the top 10% of correlations as edges [2]. Negative correlations were excluded and self-connections removed.

[2] Although based on common practices in neuroimaging, threshold choice is arbitrary and can influence results (van den Heuvel et al. 2017).

While weighted graphs retain more information, they are also more sensitive to specific correlation values, and variations in measure values are often entangled with variation in weights (Fornito et al. 2016, p. 98). Binarisation is a crude but widely used approach to remove spurious correlations and ensure comparability

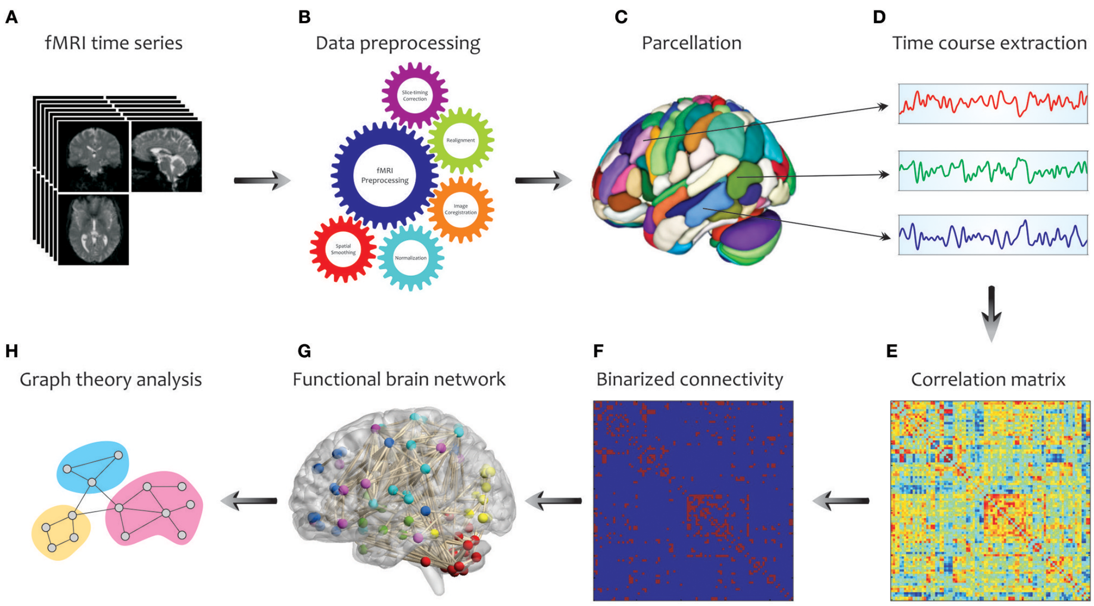



Figure 3.2: Schematic representation of brain network construction and graph theoretical analysis using fMRI data. Taken from Farahani et al. (2019). In current study: (A) Task-fMRI frames during exposure to climate-related statements framed as threat-, solution-oriented, or neutral. (B) Preprocessing using fMRIPrep 25.1.3 and XCP-D v0.13.0. (C) Whole-brain parcellation with the 4S456 atlas. (D) Extraction of parcel-wise BOLD time series. (E) Construction of condition-specific functional connectivity matrices using Pearson correlations between parcel time series. (F) Binarisation of connectivity at a threshold of 0.1. (H) Computation of global graph-theoretical measures, including global efficiency, clustering coefficient, and modularity.

across subjects and studies. Most graph measures, including those chosen in this study, are simpler and easier to interpret when computed on binary networks. Nevertheless, binarisation may eliminate important information, especially when applied to functional connectivity matrices.

Tha aim of the study was to investigate the exposure to news messages as a whole-brain-event. Subsequently, graphs were investigated using global measures. Local measures could have offered additional insight but would have required specific hypotheses about which regions or nodes are involved, which does not align with the more exploratory aim of the study. Thus, focus remains on three global measures, including *global efficiency*, *clustering coefficient* and *modularity*, chosen to capture complementary aspects of brain network organisation, from integration and segregation to stability under targeted disruptions, and are described in detail below.

**Definition 3.4.1 – Chosen Global Graph Measures**

**Global efficiency**: measures how quickly information can travel across the entire brain network, with higher values indicating more efficient integration.

**Clustering Coefficient**: measures how interconnected a node's immediate neighbours are with each other, with higher values indicating greater local segregation and specialised processing within brain regions.

**Modularity**: measures how the brain network is subdivided into distinct communities of interconnected regions, with higher values indicating stronger separation between functional modules.

### Global Efficiency

*Global Efficiency* captures the average efficiency, calculated as the multiplicative inverse of the shortest path distance between all pairs of nodes of a given graph. The measure was proposed by Latora and Marchiori (2001) to characterise small-world behaviour in a single variable. It is an inversely related measure of characteristic path length ($L$)[3] better suited for parallel as opposed to sequentially processing systems[4] (Fornito et al. 2016, p. 225).

[3] $L$ denotes the average number of edges along the shortest paths between all pairs of nodes

[4] Global efficiency is better suited for disconnected graphs. If two nodes cannot reach each other, $d(i,j) = \infty$, causing $L$ to diverge, whereas $E_{\text{glob}}$ handles this gracefully by treating $\frac{1}{d(i,j)} = 0$.

$$E_{\text{glob}}(G) = \frac{1}{N(N-1)} \sum_{i \neq j \in V} \frac{1}{d(i,j)} \tag{3.1}$$

where $N$ denotes the total number of nodes in the network, $V$ is the set of nodes, and $d(i,j)$ represents the shortest path length between nodes $i$ and $j$.

**Clustering Coefficient** Global clustering is captured using the `average_clustering` algorithm, which takes the mean of all individual nodes' local clustering coefficients $C_l(i)$ across the $N$ nodes in the network. Fornito et al. (ibid.) suggest that the clustering coefficient can be thought of as the probability of finding a connection between any two neighbours of a node. It is calculated as the ratio of the number of edges that exist between node $i$'s neighbours to the maximum number of edges that could exist between them—a method also referred to as the Watts–Strogatz clustering coefficient. It is important to note that every node is treated equally regardless of its degree; consequently, low-degree nodes carry the same weight as highly connected hubs, and their overrepresentation can inflate the global average.

$$C_l = \frac{1}{N} \sum_{i \in N} C_l(i) = \frac{1}{N} \sum_{i \in N} \frac{2t_i}{k_i(k_i - 1)} \tag{3.2}$$

where $N$ denotes the total number of nodes in the network, $C_l(i)$ is the local clustering coefficient of node $i$, $t_i$ represents the number of triangles involving node $i$, and $k_i$ is the degree of node $i$.

**Modularity** Modularity captures whether within-community connections exceed what would be expected under a null model where edges are rewired randomly while preserving node degrees. It is calculated as the difference between the observed degree of intramodule connectivity and that expected by chance in a random network (ibid.). Modules are defined using the `greedy_modularity_communities` algorithm — a Louvain-style greedy community detection approach which iteratively merges node pairs into communities if doing so increases $Q$. However, $Q_{\text{max}}$ is not guaranteed to yield a single value. Usually, a network will have a number of alternative partitions (Good et al. 2010), meaning that different runs may produce slightly varied community partitions.

$$Q = \frac{1}{2m} \sum_{ij} \left[ A_{ij} - \frac{k_i k_j}{2m} \right] \delta(c_i, c_j) \tag{3.3}$$

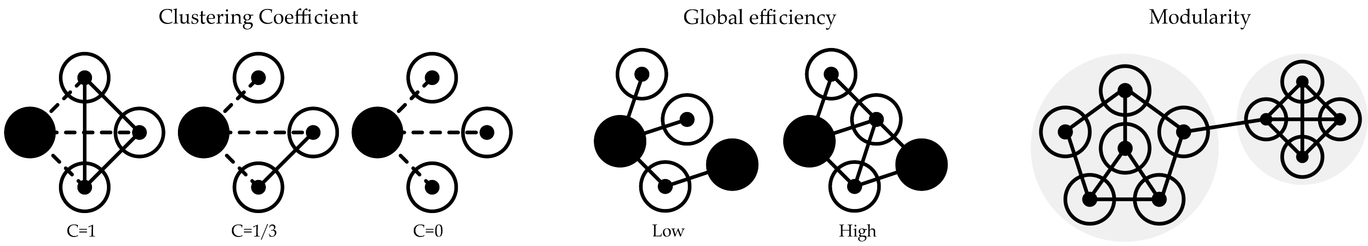



Figure 3.3: Schematic illustration of used graph measures. Adapted from Borne et al. (2024). *Graphic design by Rokas Auryla.*

### 3.4.3 *Null Models*

Values of most network measures are highly influenced by basic network properties, including nodes, links, and the degree distribution (Rubinov and Sporns 2010). To account for this, null models are used as the comparative framework to test for the significance of graph measures. In this study, the null graph was generated using the Maslov and Sneppen (2002) algorithm, implemented via `NetworkX`'s `double_edge_swap` function, which randomises the network by repeatedly swapping pairs of edges while preserving the size, density, and degree sequence of the original graph. To ensure sufficient randomisation, for each participant, 100 null graphs were generated, with the number of edge swaps set to 100 times the number of edges in the original graph.

## 3.5 *Coactivation Pattern Analysis (CAP)*

### 3.5.1 *Data Preparation*

Condition-specific graph measures provide a static summary of network organisation. Specifically, they collapse the temporal dimension of the signal into a single connectivity estimate per condition. To capture the temporal dynamics missing in graph measures, Co-Activation Pattern (CAP) analysis (Liu and Duyn 2013) was applied as the second method to investigate task-fMRI runs.

CAP analysis is a data-driven method used in fMRI research to identify recurring brain states and their transitions across framing conditions (Liu and Duyn 2013; Liu, N. Zhang et al. 2018). A state here denotes a spatial configuration of brain activity that transiently co-activates across time—in other words, a recurring pattern of BOLD signal across captured brain regions. To identify states and their measures, the `NeuroCAPs` (D. Smith 2025) package was used.

In this study, CAPs were derived from four runs: two resting-state runs acquired before and after the task, and the two task runs. The parcellation followed the same approach as in the graph measure analysis, using the 4S456 atlas in MNI152NLin2009cAsym space. A global parcel mask was constructed by excluding parcels containing NaN values in any of the four runs, retaining only parcels valid across all runs.

Prior to clustering, parcel-wise BOLD time series were $z$-scored across time to standardise signal magnitude across parcels and participants. CAPs were identified by applying $k$-means clustering to the concatenated parcel-wise BOLD time series across all participants and runs. $K$-means clustering works by partitioning observations into $k$ clusters, minimising the within-cluster variance between data points and their cluster centroids. Applied to fMRI data, each observation corresponds to the whole-brain parcellated BOLD activation pattern at a single timepoint, such that timepoints with similar spatial activation profiles are grouped into the same cluster—clusters are thus taken to represent recurring brain states. To determine the optimal number of states (CAPs), the elbow method (Yuan and Yang 2019) was applied over a range of 2 to 20 clusters. The elbow method is a heuristic approach that identifies a point (the 'elbow' ) at which extra clusters do not substantially improve the fit of the model. To facilitate neurobiological interpretation, each identified CAP was mapped onto the seven and seventeen Yeo resting-state (Yeo et al. 2011) networks using cosine similarity. Cosine similarity treats each CAP's spatial activation pattern as a vector and compares it against each network's binary mask, yielding values ranging from $-1$ to 1, where 1 indicates perfect spatial alignment, 0 indicates orthogonality, and $-1$ indicates opposite orientations.

### 3.5.2 *Temporal Metrics*

To enable condition-specific CAP analysis, time series were split by experimental condition (neutral, solution, threat) using frame-wise condition labels. For each condition, three temporal metrics were computed per participant per CAP: *temporal fraction*, *counts*, and *persistence* (Liu, N. Zhang et al. 2018). Temporal metrics were computed following the implementation provided in the `NeuroCAPS` documentation. Together, these metrics characterise the prevalence, stability, and recurrence of derived brain states, enabling comparison of condition-dependent temporal dynamics in large-scale brain organisation.

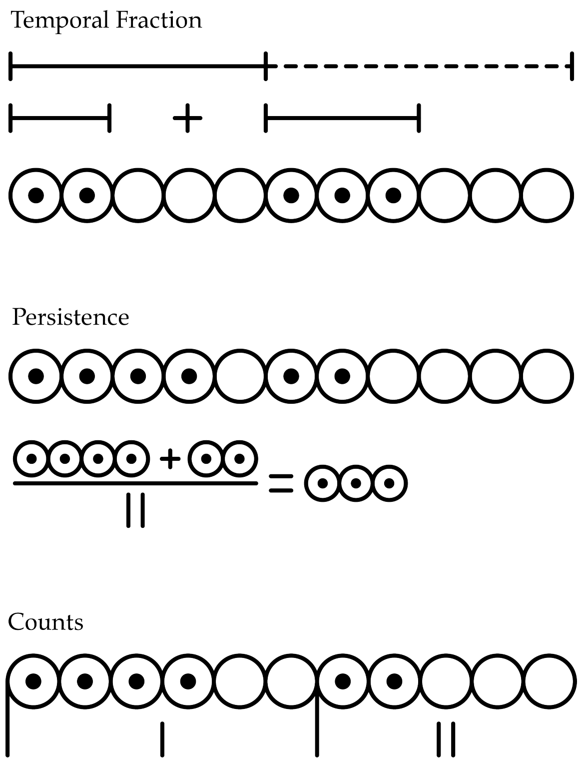



Figure 3.4: Schematic illustration of CAP temporal metrics. *Graphic design by Rokas Auryla.*

**Definition 3.5.1 – CAP Temporal Metrics**

**Temporal Fraction**: represents share of the total time points during which a specific CAP is active within a run.

**Persistence**: captures average time spent in a single CAP before transitioning to another CAP. It reflects the stability of that CAP over time.

**Counts**: trace how many times a given CAP begins during a run . A new count is recorded only when a CAP appears after a different CAP, and continuous occurrences are treated as a single initiation.

## 3.6 *Statistical Analysis*

To test for statistical differences between graph and temporal metrics across framing conditions, linear mixed-effects models were implemented using the `statsmodels` module (Skipper and Perktold 2010). Each dependent variable—graph metrics and temporal metrics per CAP—was fit with a separate model with condition entered as a fixed effect. Subject-specific random intercepts were included to account for individual differences in baseline activation levels in repeated within-subject observations . Given the relatively small sample size, models were estimated using restricted maximum likelihood (REML), which provides unbiased variance estimates by correcting for the number of estimated fixed effects. First, neutral was used as the reference condition to estimate the contrasts of threat versus neutral and solution versus neutral. To obtain the direct comparison between solution and threat, the model was subsequently refit with solution as the reference category.

For each contrast, regression coefficients, standard errors, Wald $z$-statistics, 95% confidence intervals, and associated $p$-values were extracted. To control for multiple comparisons, Benjamini–Hochberg false discovery rate (FDR) correction ($\alpha = .05$) was applied separately within each graph metric for graph analyses and separately within each CAP-specific temporal metric for CAP analyses.

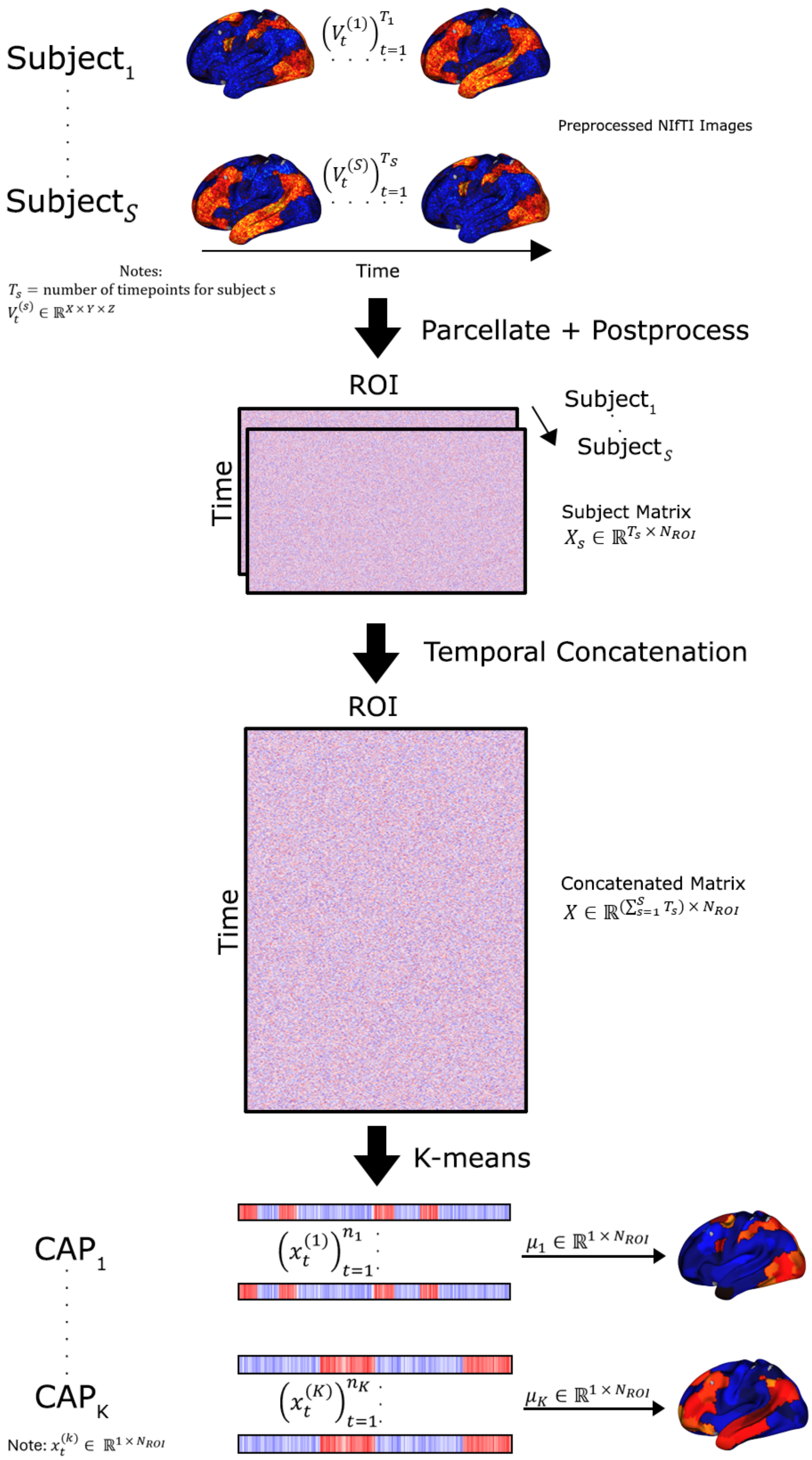



Figure 3.5: NeuroCAPs pipeline for CAP analysis. Taken from NeuroCAPs documentation (D. Smith 2025).

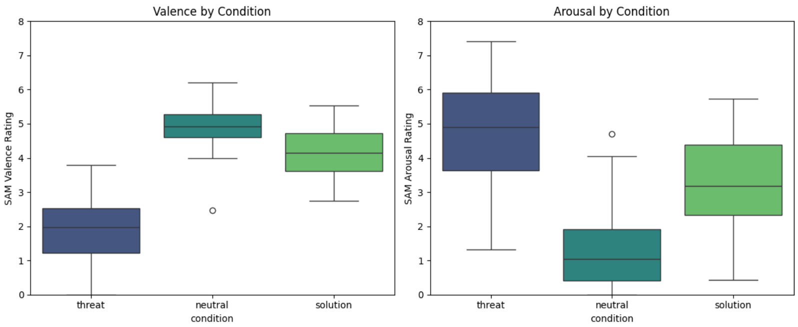
# 4
# Results

## 4.1 Manipulation Check

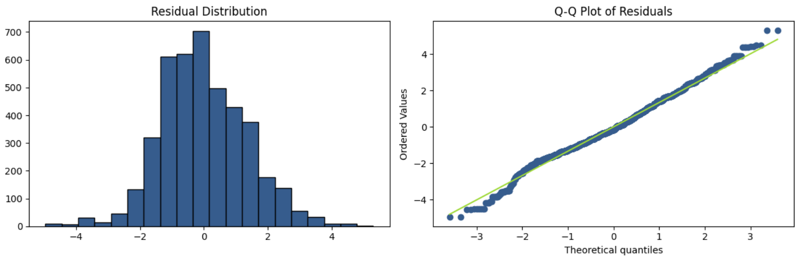
[1] For details regarding the assignment of condition labels and their validity, see (Ringhofer et al. n.d.), manuscript currently under review.

The experimental conditions were based on the premise that distinct communicative frames should evoke affectively distinct engagements. Threat, solution, and neutral labels were assigned to the statements by researchers[1]. A manipulation check was conducted to verify that participants also perceived the three conditions as affectively distinct. As shown in Boxplot 4.1a, threat statements were evaluated by participants as having lower valence and higher arousal relative to neutral and solution conditions. Compared to neutral, solution statements were also lower in valence and higher in arousal, but with a smaller contrast compared to threat vs. neutral. Subject 043's ratings were identified as outliers and excluded from subsequent manipulation check analyses; after exclusion, the normality violation was resolved (Shapiro-Wilk: $W = 0.920$, $p = .008$ before exclusion; $W = 0.972$, $p = .425$ after exclusion), as further confirmed by histogram and Q–Q plots (Figure 4.1b).

A linear mixed-effects model (REML) with subject random intercept was fit to trial-level data, using neutral as the reference condition. Results show that statement condition significantly influenced both valence and arousal ratings. Regarding valence ratings, compared to neutral, solution ($\beta = -0.83$, $SE = 0.05$, $p < .001$), and threat ($\beta = -3.08$, $SE = 0.05$, $p < .001$) statements were rated as more negative, but with a stark decrease for the threat condition. Condition also significantly influenced arousal ratings. Compared to neutral, solution ($\beta = 1.84$, $SE = 0.06$, $p < .001$) and threat statements were evaluated to be more arousing ($\beta = 3.30$, $SE = 0.06$, $p < .001$), again the latter showing a stronger increase. One-way ANOVAs on subject-level condition means yielded converging results for both valence ($F(2, 114) = 172.35$, $p < .001$, $\eta^2 = .75$) and arousal ($F(2, 114) = 56.95$, $p < .001$, $\eta^2 = .50$), with threat condition showing the strongest effect.




(a) Condition rating distributions by experimental condition.




(b) Residual diagnostics: histogram and Q–Q plot.

Figure 4.1: Normality diagnostics for the manipulation check: (a) Condition ratings boxplot, (b) Residual plots.

## 4.2 *Graph Analysis*

### 4.2.1 *Null Model Validation*

Normalised graph metrics obtained using the Maslov-Sneppen rewiring algorithm were significantly different from 1 (one-sample t-tests, all $p < .001$), indicating that observed empirical brain networks are organised non-randomly. Clustering ($mean = 2.955$) and modularity ($mean = 3.891$) score well above 1, pointing to small world architecture, where brain networks are more clustered and modular than chance. Global efficiency below 1 ($mean = 0.862$) showed that observed networks are less efficient than random, which has been observed in other studies and attributed as a cost for local specialisation (Rubinov and Sporns 2010). Pearson correlation between each participant's empirical and their normalised value (empirical / null mean) for global efficiency ($r = 0.97$, $p = .000$) and modularity ($r = 0.95$, $p = .000$) was close to 1, illustrating that normalised value norm is just a linear rescaling of the raw value. For clustering, however, the null correction reverses the direction ($r = -0.314$, $p = 0.002$) indicating that raw clustering differences between participants are driven by degree/density differences [2].

[2] The Maslov-Sneppen algorithm preserves each participant's degree sequence only *within* their own null model. It serves as an individual baseline.

### 4.2.2 *Graph Metrics*

For the most part, investigated graph metrics: global efficiency, clustering and modularity showed no significant difference among compared conditions. Using linear mixed model estimated with REML and subject random intercept, the only significant result after FDR correction was lower global efficiency during threat versus neutral ($\beta = -0.00479$, $p = .015$, FDR-corrected $p = .044$). A similar result for global efficiency was observed for the solution versus neutral contrast ($\beta = -0.00405$, $p = .039$); however, this value did not survive FDR correction (FDR-corrected $p = .059$), raising a possibility that it could emerge simply due to multiple comparisons. Clustering showed weak positive trends for both threat ($\beta = 0.00934$, $p = .054$, FDR-corrected $p = .082$) and solution ($\beta = 0.01003$, $p = .039$, FDR-corrected $p = .082$) relative to neutral, but neither survived FDR correction. Modularity showed no reliable effects across conditions, all of which remained non-significant. Overall, the contrast between threat and solution for all investigated graph measures seems to be insubstantial.

| Metric | Contrast | Reference | $\beta$ | SE | $z$ | $p$ | $p_{FDR}$ |
|---|---|---|---|---|---|---|---|
| Global efficiency | Threat | Neutral | −0.005 | 0.002 | −2.44 | .015* | .044* |
| | Solution | Neutral | −0.004 | 0.002 | −2.06 | .039* | .059 |
| | Threat | Solution | −0.001 | 0.002 | −0.38 | .705 | .705 |
| Clustering | Threat | Neutral | 0.009 | 0.005 | 1.92 | .054 | .082 |
| | Solution | Neutral | 0.010 | 0.005 | 2.07 | .039* | .082 |
| | Threat | Solution | −0.001 | 0.005 | −0.14 | .887 | .887 |
| Modularity | Threat | Neutral | −0.006 | 0.010 | −0.57 | .570 | .570 |
| | Solution | Neutral | 0.007 | 0.010 | 0.67 | .503 | .570 |
| | Threat | Solution | −0.013 | 0.010 | −1.24 | .216 | .570 |

$^{*}p < .05$

Table 4.1: Linear mixed-effects model (REML) results for empirical graph metrics.

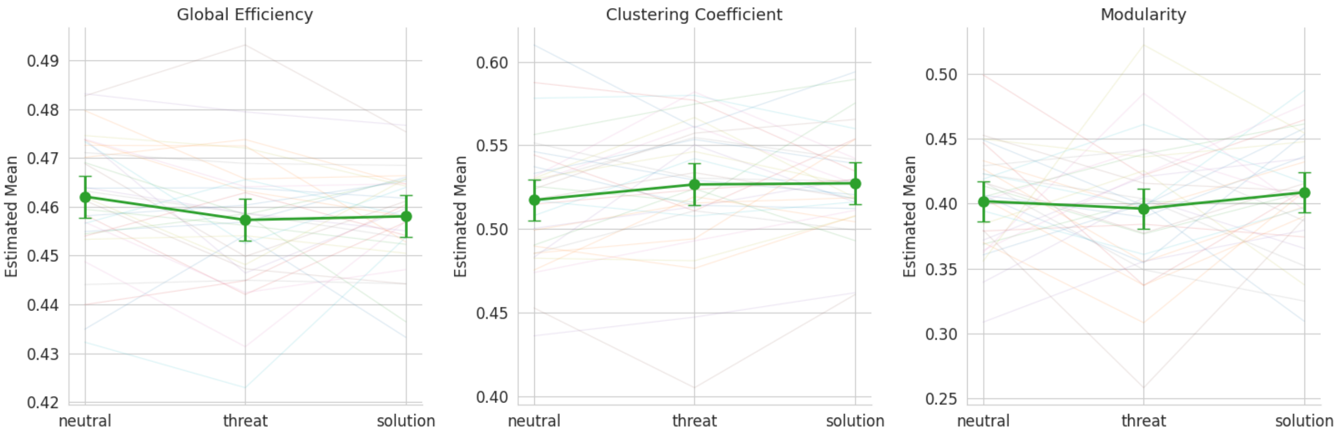
The same linear mixed model (REML) with subject as random factor was also applied to normalised graph metric values. In this case, global efficiency contrast relative to neutral was found to be significant after FDR correction for solution ($\beta = -0.00701$, $p = .030$, FDR-$p = .045$) as well as threat ($\beta = -0.00812$, $p = .012$, FDR-$p = .036$). A notable shift for normalised value metrics compared to empirical values appears for clustering. Whereas previously clustering showed weak positive trends for both threat and solution relative to neutral with effects that were significant or close to significant prior to FDR correction, after accounting for normalisation, these effects disappear (solution: $\beta = -0.03052$, $p = .622$, FDR-$p = .622$, threat: $\beta = -0.12431$, $p = .045$, FDR-$p = .134$). This is a clear indication that previously observed clustering trends are not robust to the normalization procedure, consistent with the previous null model validation indicating that raw clustering differences are driven by degree/density differences between participants.

| Metric | Contrast | Reference | $\beta$ | SE | $z$ | $p$ | $p_{FDR}$ |
|---|---|---|---|---|---|---|---|
| Global efficiency | Threat | Neutral | −0.008 | 0.003 | −2.51 | .012* | .036* |
| | Solution | Neutral | −0.007 | 0.003 | −2.17 | .030* | .045* |
| | Threat | Solution | −0.001 | 0.003 | −0.34 | .732 | .732 |
| Clustering | Threat | Neutral | −0.124 | 0.062 | −2.01 | .045* | .134 |
| | Solution | Neutral | −0.031 | 0.062 | −0.49 | .622 | .622 |
| | Threat | Solution | −0.094 | 0.062 | −1.51 | .130 | .195 |
| Modularity | Threat | Neutral | −0.008 | 0.095 | −0.08 | .935 | .935 |
| | Solution | Neutral | 0.089 | 0.095 | 0.94 | .347 | .521 |
| | Threat | Solution | −0.097 | 0.095 | −1.02 | .307 | .521 |

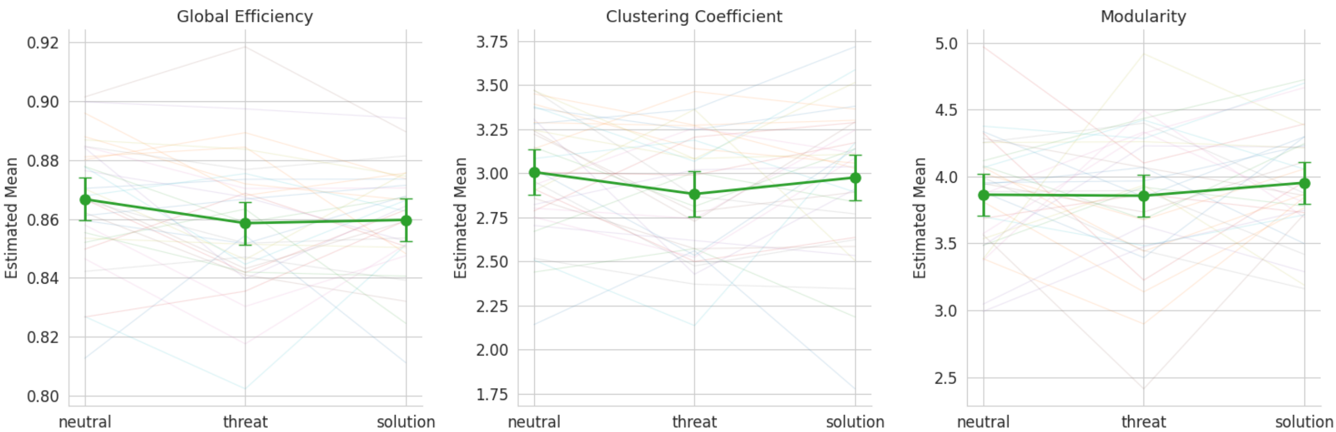
$^{*}p < .05$

Table 4.2: Linear mixed-effects model (REML) results for normalised graph metrics.

Looking at Estimated Marginal Means Plots for both empirical (Figure 4.2a) and normalised values (Figure 4.2b), it is visually striking that individual trajectories show larger changes across conditions than the bold estimated means across participants. This observation suggests that means averaging is potentially smoothing over meaningful individual variability. One likely scenario, based on the plots, is that opposing response patterns across subjects, where one participant shows a lower value for a given metric in a condition while another shows a higher value, partially cancel each other out when averaged. The resulting group mean change may appear small, even in the case where individual metrics show more substantial shifts.




(a) Estimated Marginal Means Across Conditions for **Empirical** Values




(b) Estimated Marginal Means Across Conditions for **Normalised** Values

Figure 4.2: Model Estimated Marginal Means (EMMs) Plots: (a) empirical values, (b) normalised values. Faint lines depict individual trajectories across conditions.

To summarise, global efficiency showed a small but reliable decrease in threat relative to neutral conditions and a weaker but similar pattern for solution, with no robust effects for clustering or modularity. While group-level condition differences were generally small and except for global efficiency non-significant, plotted individual trajectories suggest considerable inter-individual variability in the magnitude and direction of condition-related changes, indicating heterogeneous network responses across participants.

## 4.3 *Coactivation Pattern Analysis (CAPs)*

### 4.3.1 *Identification of CAPs*

CAPs were derived on parcellated brain maps defined by Schaefer's 400 cortical regions together with subcortical parcels. Prior to CAP estimation, subject-specific validity masks were intersected to form a group-level mask retaining only parcels with no missing values across all subjects, resulting in a final set of 344 valid nodes used for CAP analysis. Subsequently, seven ($K = 7$) distinct brain states (CAPs) were identified, reflecting recurring patterns of co-activated brain activity across the combined fMRI dataset, including pre-task and post-task resting-state, as well as both task A and B runs.

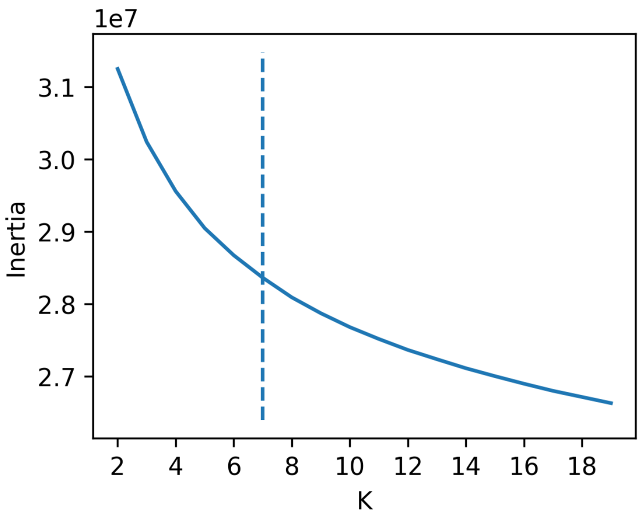
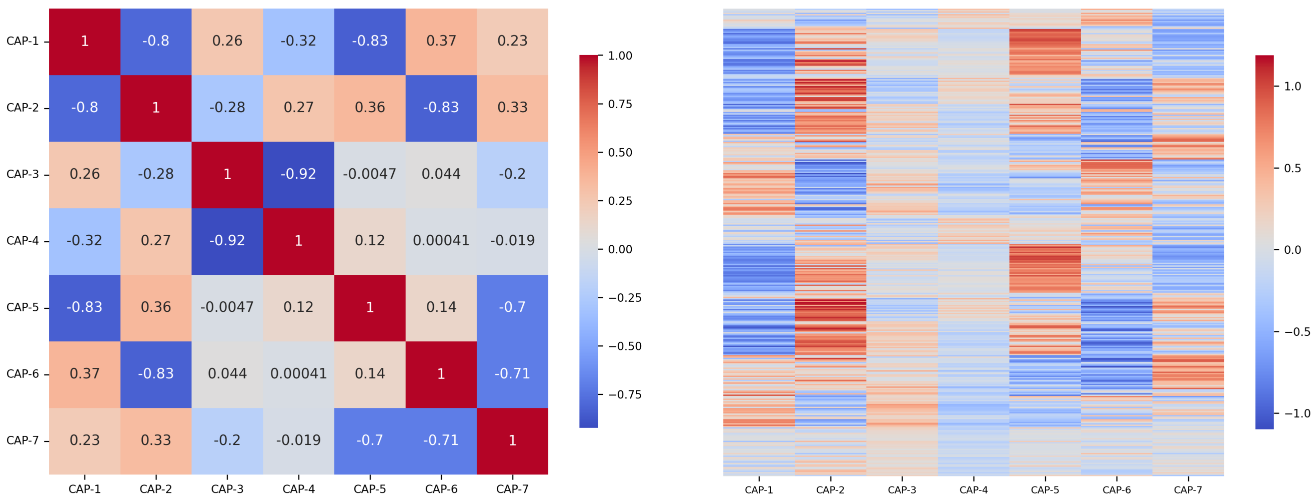



Figure 4.3: Elbow method for determining the optimal number of clusters (K). The dashed vertical line indicates the selected solution at K = 7, corresponding to the point of diminishing returns in inertia reduction.




(a) CAPs Correlation Matrix

(b) CAPs Heatmap (Nodes)

Figure 4.4: CAPs Spatial Patterns: (a) Correlation matrix (b) Heatmap of CAP activations across nodes.

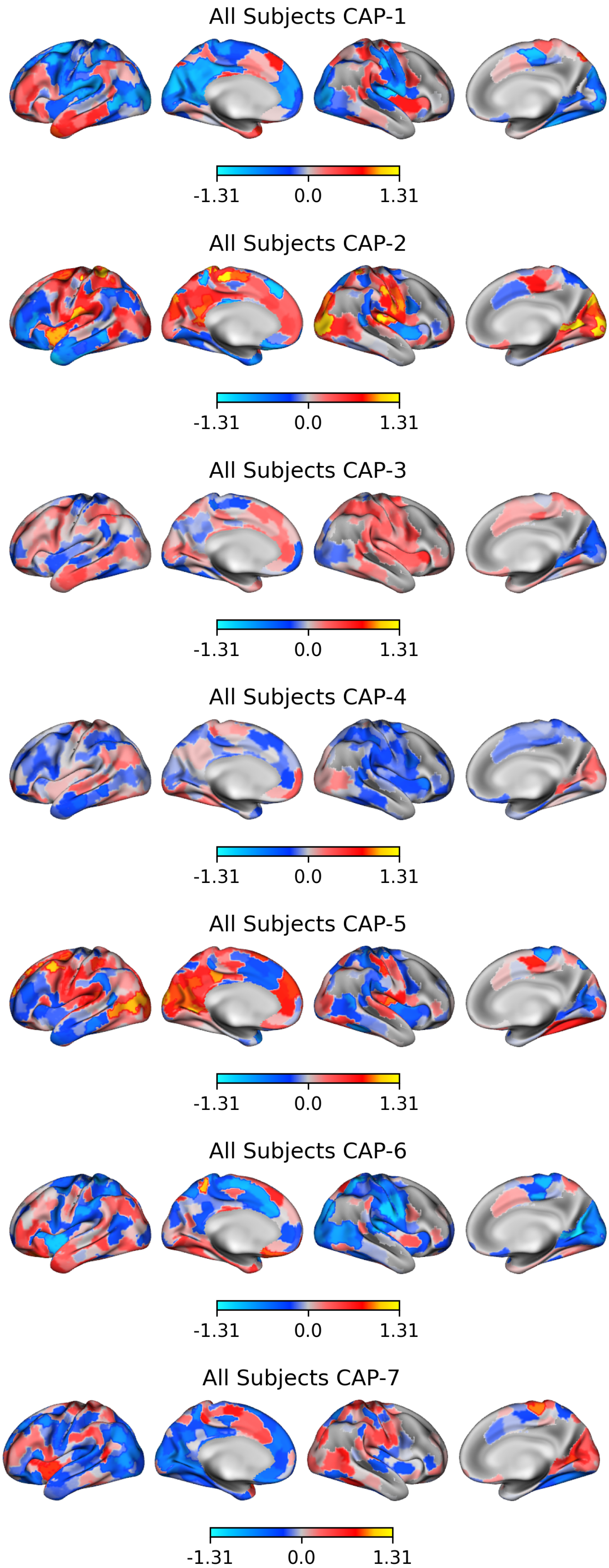
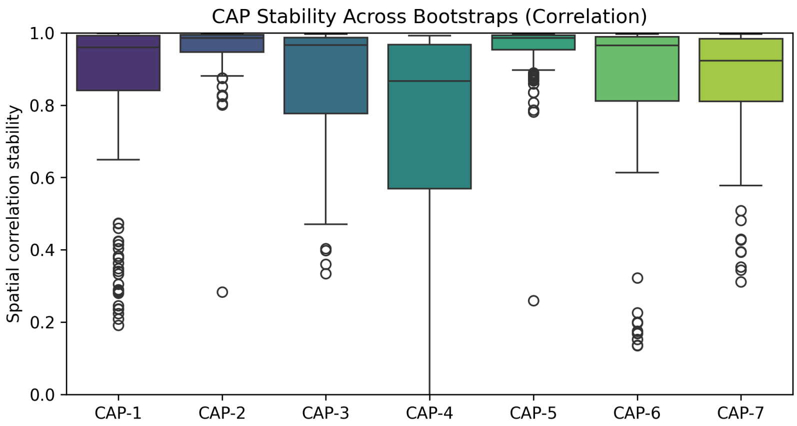
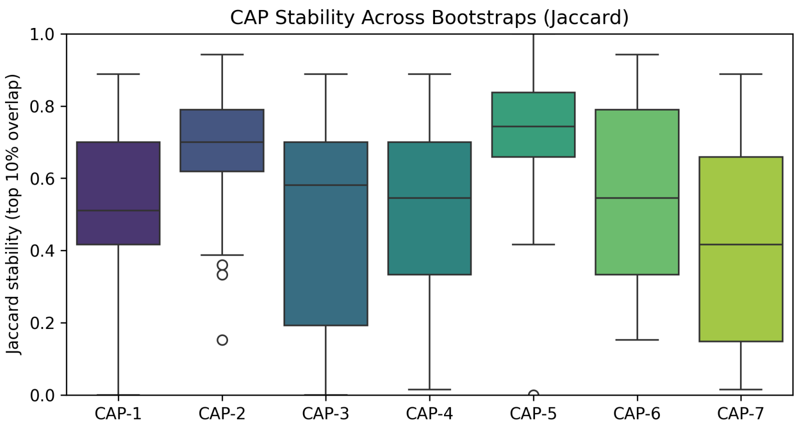



Figure 4.5: Surface plots of each CAP projected onto the cortical surface. Colours indicate the mean BOLD signal deviation from the global mean, with warm colours (red–yellow) reflecting positive activation and cool colours (cyan–blue) reflecting deactivation. Each CAP is shown from four views: left lateral, left medial, right lateral, and right medial.

To evaluate the stability of the identified CAPs across different participant subsets from two angles, correlation and bootstrap analyses were performed to test for spatial and temporal CAP stability. CAP-wise spatial correlation stability was consistently high across CAPs (CAP 1 to CAP 7: 0.861, 0.964, 0.872, 0.726, 0.963, 0.876, and 0.874), yielding an overall mean correlation stability of 0.8765. CAP-wise Jaccard stability values were lower (0.528, 0.693, 0.475, 0.520, 0.728, 0.547, 0.409) with a mean Jaccard stability of 0.557. Regarding individual CAPs, CAP2 and CAP5 were found to be the most stable ones. Together, these results indicate that while the $K = 7$ solution captures spatial patterns that are relatively robust, the boundaries between states show moderate variability across bootstrap samples.




(a) Spatial correlation stability of the $K = 7$ CAPs across bootstrap samples. Circles show outliers.




(b) Jaccard stability of the $K = 7$ CAPs across bootstrap samples.

Figure 4.6: Bootstrap stabilities of the $K = 7$ CAPs: (a) Correlation stability, (b) Jaccard stability.

To explore the functional significance of the identified CAPs, spatial correspondence with the Yeo 7- and 17-network parcellations was assessed at the parcel level. CAP–network similarity was quantified by calculating cosine similarity of individual CAPs to Yeo-17 functional networks, and later grouping of those values by Yeo-7 parcellation. Radar plots below display CAP–network correspondence with mean positive and negative CAP activations within each functional network.

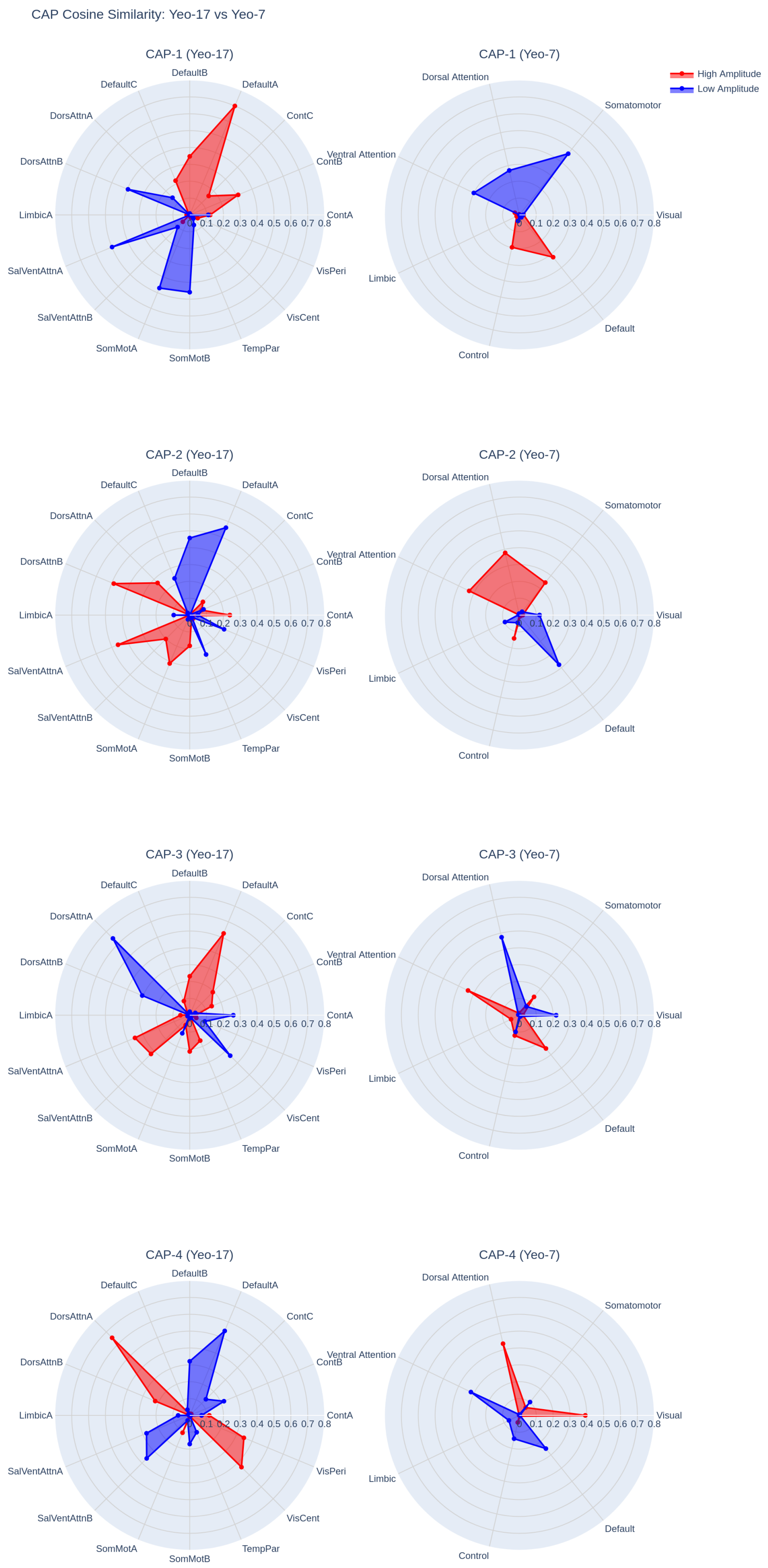



Figure 4.7: Radar plots displaying cosine similarity between each CAP and brain networks defined by Yeo-17 (left) and Yeo-7 (right) parcellations (CAPs 1–4). Red represents positive cosine similarity values, blue—negative cosine similarity values.

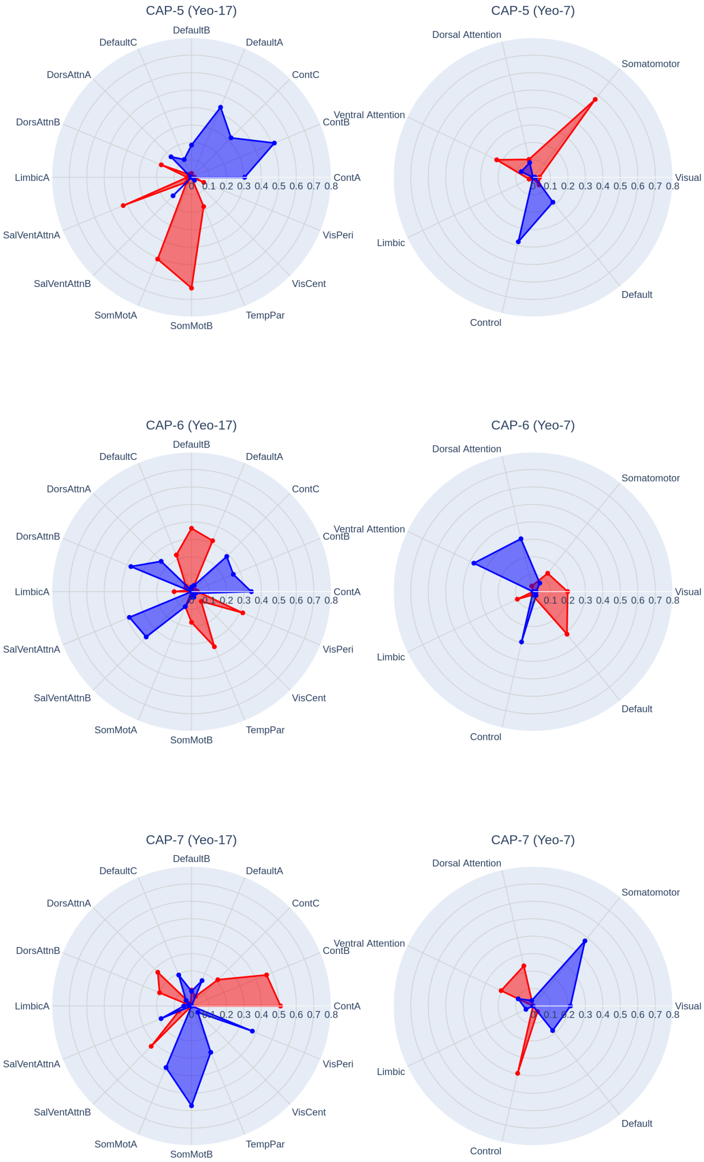



Figure 4.8: Radar plots displaying cosine similarity between each CAP and brain networks defined by Yeo-17 (left) and Yeo-7 (right) parcellations (CAPs 5–7). Red represents positive cosine similarity values, blue—negative cosine similarity values.

### 4.3.2 CAP Temporal Dynamics

Condition-dependent CAP dynamics were assessed using linear mixed-effects models (REML) with subject-specific random intercepts, separately for counts, temporal fraction, and persistence. The only significant result to survive FDR correction was higher CAP5 count for solution condition relative to threat ($\beta = 1.69$, $p = .003$, $p_{\text{FDR}} = .013$). CAP5 also showed higher temporal fraction compared to threat, although given threshold bordering $p$, significance was rejected after multiple comparisons ($\beta = 0.019$, $p = .046$, $p_{\text{FDR}} = .084$). A similar pattern was observed for CAP2, where temporal fraction was higher in the solution condition relative to neutral ($\beta = 0.020$, $p = .024$, $p_{\text{FDR}} = .072$). CAP3 showed an opposite direction of effect, with reduced count ($\beta = -1.437$, $p = .021$, $p_{\text{FDR}} = .072$) and temporal fraction ($\beta = -0.026$, $p = .037$, $p_{\text{FDR}} = .094$) in the solution condition relative to neutral. However, neither CAP2 nor CAP3 results survived FDR correction. Regarding persistence, no significant effects were observed.

Overall, only three CAPs: CAP2, CAP3, and CAP5; showed significant condition-dependent effects on temporal dynamics, with only CAP5 contrast between solution and threat remaining significant after multiple-comparison correction. The relatively higher reported stability of CAP2 and CAP5 among identified CAPs (Jaccard stability = 0.693 and 0.728, respectively) likely contributes to their prevalence in condition-dependent temporal effects, where none have been found for others.

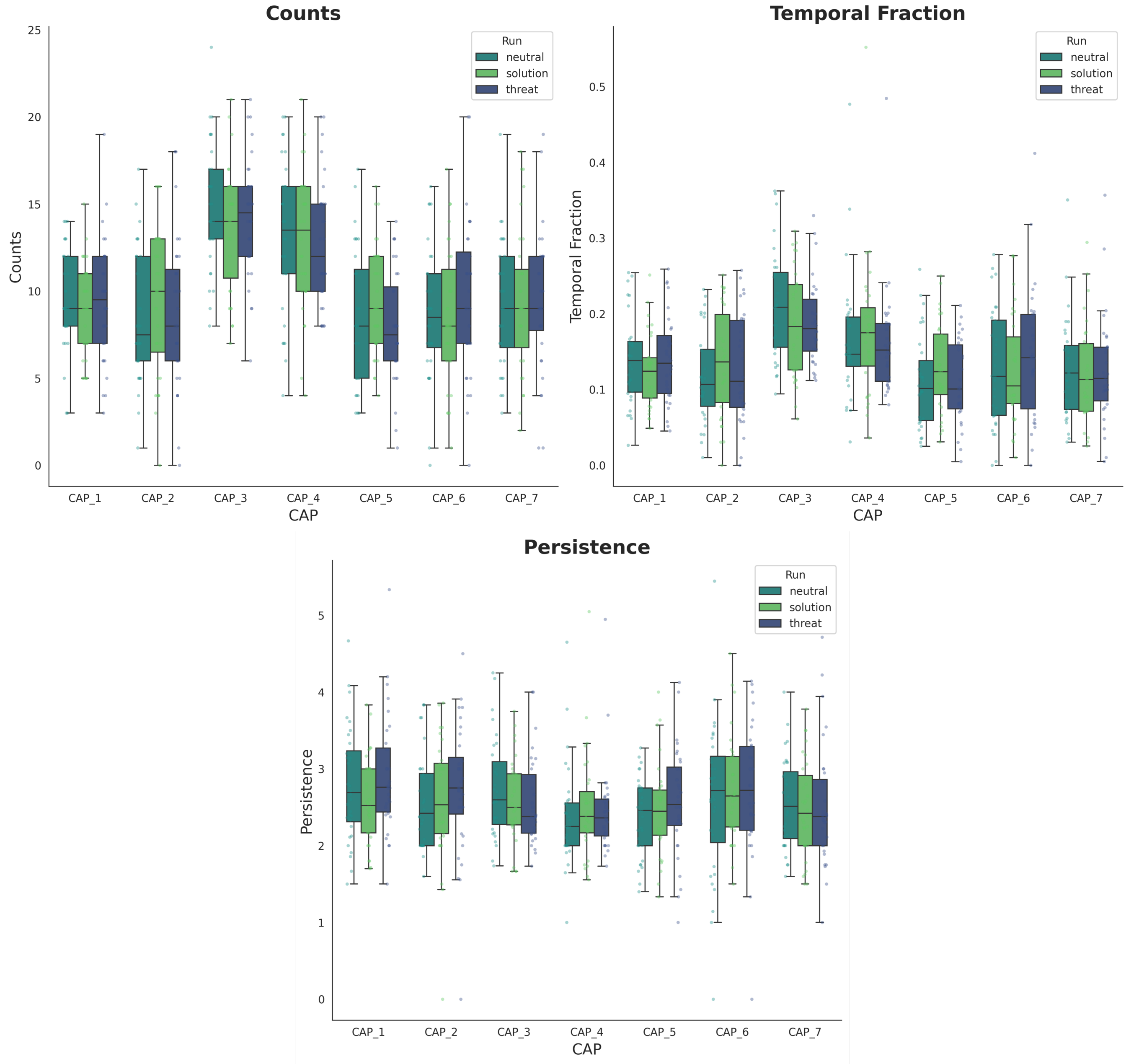



Figure 4.9: Box Plot Distribution of CAP temporal metrics across seven brain states and three framing conditions. Boxes show interquartile range; jittered points represent individual participants.

| Metric | CAP | Contrast | Reference | $\beta$ | SE | $z$ | $p$ | $p_{FDR}$ |
|---|---|---|---|---|---|---|---|---|
| Temporal fraction | CAP 1 | Threat | Neutral | −0.000 | 0.011 | −0.01 | .996 | .996 |
| | | Solution | Neutral | −0.016 | 0.011 | −1.36 | .175 | .265 |
| | | Solution | Threat | −0.015 | 0.011 | −1.35 | .177 | .265 |
| | CAP 2 | Threat | Neutral | 0.014 | 0.009 | 1.53 | .126 | .190 |
| | | Solution | Neutral | 0.020 | 0.009 | 2.26 | .024* | .072 |
| | | Solution | Threat | 0.007 | 0.009 | 0.73 | .467 | .467 |
| | CAP 3 | Threat | Neutral | −0.024 | 0.013 | −1.86 | .063 | .094 |
| | | Solution | Neutral | −0.026 | 0.013 | −2.08 | .037* | .094 |
| | | Solution | Threat | −0.003 | 0.013 | −0.22 | .825 | .825 |
| | CAP 4 | Threat | Neutral | −0.003 | 0.011 | −0.32 | .746 | .746 |
| | | Solution | Neutral | 0.010 | 0.011 | 0.91 | .360 | .540 |
| | | Solution | Threat | 0.013 | 0.011 | 1.24 | .215 | .540 |
| | CAP 5 | Threat | Neutral | −0.001 | 0.010 | −0.08 | .936 | .936 |
| | | Solution | Neutral | 0.019 | 0.010 | 1.91 | .056 | .084 |
| | | Solution | Threat | 0.019 | 0.010 | 1.99 | .047* | .084 |
| | CAP 6 | Threat | Neutral | 0.016 | 0.011 | 1.44 | .151 | .227 |
| | | Solution | Neutral | −0.003 | 0.011 | −0.24 | .809 | .809 |
| | | Solution | Threat | −0.019 | 0.011 | −1.68 | .094 | .227 |
| | CAP 7 | Threat | Neutral | −0.002 | 0.009 | −0.25 | .805 | .814 |
| | | Solution | Neutral | −0.004 | 0.009 | −0.48 | .630 | .814 |
| | | Solution | Threat | −0.002 | 0.009 | −0.23 | .814 | .814 |
| Counts | CAP 1 | Threat | Neutral | −0.063 | 0.676 | −0.09 | .926 | .926 |
| | | Solution | Neutral | −0.500 | 0.676 | −0.74 | .460 | .777 |
| | | Solution | Threat | −0.438 | 0.676 | −0.65 | .518 | .777 |
| | CAP 2 | Threat | Neutral | 0.250 | 0.618 | 0.40 | .686 | .686 |
| | | Solution | Neutral | 1.031 | 0.618 | 1.67 | .095 | .286 |
| | | Solution | Threat | 0.781 | 0.618 | 1.26 | .207 | .310 |
| | CAP 3 | Threat | Neutral | −0.469 | 0.623 | −0.75 | .452 | .452 |
| | | Solution | Neutral | −1.438 | 0.623 | −2.31 | .021* | .063 |
| | | Solution | Threat | −0.969 | 0.623 | −1.55 | .120 | .180 |
| | CAP 4 | Threat | Neutral | −0.469 | 0.738 | −0.64 | .525 | .767 |
| | | Solution | Neutral | −0.250 | 0.738 | −0.34 | .735 | .767 |
| | | Solution | Threat | 0.219 | 0.738 | 0.30 | .767 | .767 |
| | CAP 5 | Threat | Neutral | −0.719 | 0.593 | −1.21 | .225 | .225 |
| | | Solution | Neutral | 0.969 | 0.593 | 1.63 | .102 | .153 |
| | | Solution | Threat | 1.688 | 0.593 | 2.85 | .004* | .013* |
| | CAP 6 | Threat | Neutral | 0.875 | 0.622 | 1.41 | .159 | .239 |
| | | Solution | Neutral | −0.063 | 0.622 | −0.10 | .920 | .920 |
| | | Solution | Threat | −0.938 | 0.622 | −1.51 | .132 | .239 |
| | CAP 7 | Threat | Neutral | 0.063 | 0.606 | 0.10 | .918 | .918 |
| | | Solution | Neutral | 0.156 | 0.606 | 0.26 | .797 | .918 |
| | | Solution | Threat | 0.094 | 0.606 | 0.15 | .877 | .918 |
| Persistence | CAP 1 | Threat | Neutral | 0.108 | 0.167 | 0.65 | .518 | .518 |
| | | Solution | Neutral | −0.191 | 0.167 | −1.15 | .252 | .378 |
| | | Solution | Threat | −0.299 | 0.167 | −1.79 | .073 | .219 |
| | CAP 2 | Threat | Neutral | 0.169 | 0.155 | 1.09 | .275 | .522 |
| | | Solution | Neutral | 0.024 | 0.155 | 0.15 | .879 | .879 |
| | | Solution | Threat | −0.145 | 0.155 | −0.94 | .348 | .522 |
| | CAP 3 | Threat | Neutral | −0.168 | 0.139 | −1.21 | .226 | .391 |
| | | Solution | Neutral | −0.156 | 0.139 | −1.12 | .261 | .391 |
| | | Solution | Threat | 0.012 | 0.139 | 0.09 | .932 | .932 |
| | CAP 4 | Threat | Neutral | 0.070 | 0.117 | 0.59 | .553 | .691 |
| | | Solution | Neutral | 0.116 | 0.117 | 0.99 | .321 | .691 |
| | | Solution | Threat | 0.047 | 0.117 | 0.40 | .691 | .691 |
| | CAP 5 | Threat | Neutral | 0.194 | 0.144 | 1.35 | .177 | .531 |
| | | Solution | Neutral | 0.075 | 0.144 | 0.52 | .600 | .600 |
| | | Solution | Threat | −0.118 | 0.144 | −0.82 | .409 | .600 |
| | CAP 6 | Threat | Neutral | 0.135 | 0.160 | 0.84 | .399 | .681 |
| | | Solution | Neutral | 0.120 | 0.160 | 0.75 | .454 | .681 |
| | | Solution | Threat | −0.015 | 0.160 | −0.09 | .925 | .925 |
| | CAP 7 | Threat | Neutral | −0.044 | 0.137 | −0.32 | .748 | .752 |
| | | Solution | Neutral | −0.087 | 0.137 | −0.64 | .524 | .752 |
| | | Solution | Threat | −0.043 | 0.137 | −0.32 | .752 | .752 |

Table 4.3: Linear mixed-effects model (REML) results for CAP temporal metrics. $^{*}p < .05$

# 5 Discussion

> *Contrary to what phenomenology — which is always phenomenology of perception — has tried to make us believe, contrary to what our desire cannot fail to be tempted into believing, the thing itself always escapes.*
>
> —Derrida 1978, p.7

In chapter 2, I have argued that the meaning of the text is not fixed by the words on the page, but brought forth by the reader through engagement with the text. A communicative frame denotes how a message is structured. The actualised frame—how text is made sense of—is always an interpretative blend of how the message was communicated and how it was read. The unfolding of the interaction hinges on the content of the text as well as the reader's history-dependent ongoing state. The *ongoing state* here refers to the entire body, whether one is tired, sleepy, joyous, menstruating, angry etc., as well as the state of the nervous system more specifically. In this study, the brain is treated as the primary locus of investigation. As was hopefully made clear in the presentation of the enactivist-inspired philosophy, this should not be mistaken for an argument that meaning is to be found in the neural structure. It is neither a theoretical claim nor an empirical aim of this study. My interest lies in the process of sense-making. Large-scale brain dynamics are treated as an experimentally accessible level of cognitive-affective shifts reflective of sense-making.

Accordingly, this chapter is dedicated to the discussion of the derived condition-specific functional brain network metric results, in relation to the dynamical system under investigation—the brain; and the broader relational process of textual understanding. I start with the question of how well the experimental manipulation of communicative frames was received by the participants and then move on to the interpretation of the results, first addressing lower global efficiency during exposure to climate change-related statements, before moving on to characterise CAP5, and how graph metrics are to be brought into one interpretative picture with CAPs. Finally, I outline future directions for research needed to address the limitations of the present study and its generative conclusions.

## 5.1 *Frame Met: Partially Matching Interpretations*

Behind every study lies a hope that conditions constructed by the experimenter are met by the participant in the manner intended. Agreement on the interpretation, of course, is never a given. Our experiment was set up for climate-related communicative frames to be reliably read as neutral, solution-oriented, or threat-oriented statements. Looking at the condition rating distributions, participants, on average, did rate threat statements as the most aversive (low valence) and evoking the strongest feelings (high arousal) compared to other conditions. However, threat statement evaluations also had the greatest value range, showcasing substantial variability in how threat frames were met by individual participants. This is a first substantial hint that group metrics gloss over noteworthy individual variability.

Valence and arousal rating distributions also illustrate that the biggest felt affective contrast was between threat and neutral, not between solution and threat frames. Given that neutral frames on average were evaluated more positively compared to solutions, it could be said that the direction towards more explicit climate change topics was accompanied by a shift towards perceived stronger and more negative affective states. This suggests that the climate-change theme is by itself an affectively salient topic. I theorised that *Climate Change* can be conceived as a socially concretised object, where disturbances in the immediate environment get caught up in the discourse that produces its own anxieties. This perspective is reflected in the discussed participant ratings.

The discrepancy between third-person measurement and self-reported evaluation of the affective state is a known and debated issue in psychological sciences (Evers et al. 2014; Mauss and Robinson 2009). For example, in a classical fMRI study of reappraisal (McRae et al. 2008), men and women reported similar decreases in negative emotion, despite differing gender-based neural patterns. It is thus often concluded that self-reports and neural measures capture different aspects of the affective experience, and are not necessarily expected to converge in all of the experiments [1].

[1] Following Di Paolo, Cuffari et al. (2018, p.193), it could also be argued that the discrepancy between SAM ratings and neural patterns arises due to linguistic autonomy. While linguistic bodies are continuations of sensorimotor bodies, they are primarily made of utterances, acts which 'live' in a network of relations between utterances.

F. Varela (1996) was addressing a similar problem when he proposed neurophenomenology—a research program that brings first-person phenomenological accounts and third-person neuroscientific data together by treating them as mutual constraints. SAM affect ratings are not proper phenomenological accounts. They are still first-person evaluations of the investigated state. Affect is not merely a sum of physiological responses, but a lived and embodied process of sense-making (Colombetti 2014). Thus, if there is a discrepancy between observed and reported measures, both supposedly aimed at capturing the same affect, third-person measure interpretation requires consideration that the reported state might be enacted at a level not accessible with the chosen empirical measure.

So far, I have argued for the relevance of neurodynamics as a site of investigation: although meaning emerges through agent–environment coupling rather than in an isolated brain, processes of understanding are continuously shaped and constrained by ongoing neural dynamics. By turning the measure towards the functional brain network configurations, I aimed to capture the cognitive-affective state on a site through which affective sense-making becomes enacted materially[2] and experimentally accessible. The remainder of this chapter is dedicated to potential interpretations of the results in light of this enactive-inspired proposition, and to methodological caveats that must be accounted for in making these arguments.

[2] My argument here rests on the idea that thought's only materiality (without necessarily equating thought with the material) are the processes in the brain and body during its duration.

## 5.2 *Results: Significance Beyond Statistical Significance and the Signs Without Significance*

### 5.2.1 *Graph Metrics: Topological Efficiencies*

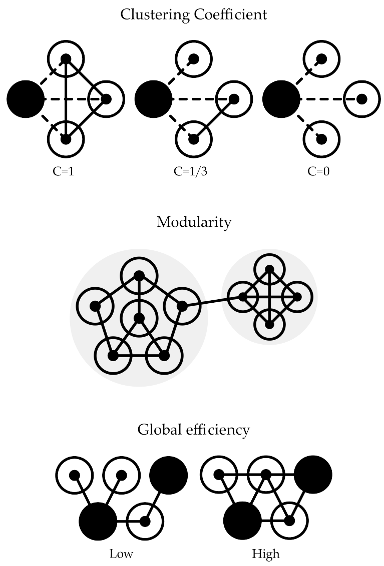



Figure 5.1: Schematic representations of graph metrics.

The only robust finding from graph-theoretical analysis was lower *global efficiency* ($E_{\text{glob}}$) during threat and solution conditions compared to the neutral baseline. Neither *modularity* ($Q$) nor *clustering coefficient* ($C_l$)[3] showed significant condition-dependent modulation. Global efficiency measures of the speed of information integration across the entire brain. In more formal terms, it is the average inverse of the shortest path length between all pairs of nodes in the network (Latora and Marchiori 2001). Clustering coefficient meanwhile captures the density of connections among a node's immediate neighbours, and modularity the degree of network subdivision into distinct modules—lack of difference between conditions showcases that the structure of the strongest correlations remained similar on regional and subsystem levels. In other words, it appears that frame conditions modulated between-module synchronisation rather than reorganising modules themselves.

[3] Clustering coefficient ($C_l$) was calculated only as a global average and local clustering was not investigated, it is also possible that local clustering did change, but in different directions across the network. Such heterogeneous changes could cancel out at the global level, resulting in no observable effect.

In the present study, graphs were derived from binarised functional connectivity matrices, in which edges represented the top 10% of the strongest Pearson correlations between parcellated brain regions. These correlations quantify the degree to which regional BOLD time series fluctuated together during a given condition. Critically, paths in the correlation-derived graphs do not represent literal anatomical or functionally causal routes. A path between two nodes is a topological abstraction derived from patterns of statistical dependency [4]. The analysed graphs were thresholded and binarised [5], which entails that all weaker correlations amount to no path; and thus the shortest path is measured not in weighted cost but in number of hops. Consequently, higher global efficiency is not evidence of biologically faster, metabolically cheaper, or causally more effective neural communication[6]. What it reflects is a more globally integrated topological organisation of functional covariance patterns.

[4] This distinction is particularly important in correlation-based functional connectivity, where Pearson correlation captures only linear statistical dependence and remains sensitive to indirect effects, including shared inputs and polysynaptic influences (Fornito et al. 2016). Moreover, correlation-based connectivity does not distinguish between phase and amplitude coupling, assumes stationarity across the analysed time window, and is intrinsically undirected, providing no information regarding causal directionality.

[5] Binary networks have also been reported to have large test–retest variability for global measures (Ran et al. 2020)

[6] For a critical discussion of the use of the "efficiency" concept, see (Poldrack 2015).

Regarding value magnitude, captured shifts in global efficiency were subtle. The magnitude of change corresponded to around 1% reduction in global efficiency relative to neutral baseline.

| | Neutral $E_{\text{glob}}$ | Threat $\beta$ | Solution $\beta$ |
|---|---|---|---|
| Empirical | 0.867 | -0.008 | -0.007 |
| Normalised | 0.462 | -0.005 | -0.004 |

Global graph measures track changes in brain-wide[7] network correlations over short windows of text exposure. Even small changes should not be underes-

[7] With the limits of what was covered by the atlas and received proper coverage during measurement. For details, see Methods.

timated and may be taken to reflect condition-relevant alterations in large-scale integration. At the same time, it should not be overstated as evidence that global efficiency captured the underlying cognitive-affective state. Neither $E_{glob}$ nor any of the other graph measures capture the difference between threat and solution prominent in SAM Valence and Arousal ratings. This discrepancy might just be the distinction, already discussed in this chapter, between third-person measurement and self-reported evaluation. It could also reflect methodological limitations, including the short temporal windows available for connectivity estimation and information loss introduced by proportional binarisation of connectivity matrices, which likely obscure more fine-grained shifts. Alternatively, based on the studies measuring global efficiency that have often reported higher network integration as the cognitive load increases (see Box 5.2.1), lower global efficiency could indicate that neutral statements might have been more challenging to read.

**Task-Modulated Changes in Global Efficiency**

In one of the earlier studies, using magnetoencephalographic data on a working memory task, greater cognitive effort led to the emergence of a more globally efficient, less clustered, and less modular network configuration (Kitzbichler et al. 2011). Modulation of network efficiency across different brain rhythms was further demonstrated by Huang et al. (2016), who found increased global efficiency during a play task relative to rest, and by Ren et al. (2017), who showed that more difficult tasks were associated with higher global efficiency and lower clustering. The same pattern of increased global efficiency and reduced clustering with greater cognitive load was also reported using fMRI data by Di et al. (2013), who compared meta-analytic coactivation networks with resting-state networks, and by H. Zhang et al. (2023), working with resting-state, working memory 1-back and 2-back tasks, further supporting the claim that task performance is accompanied by more efficient global information transmission. This change is also observed in aging with decreased efficiency for semantic cognition (Martin et al. 2023).

However, a recent study found that global properties of assortativity, global efficiency, and transitivity all decreased during task conditions (emotion and working memory) relative to rest (W. Zhang et al. 2020). One embodied EEG experiment took a slightly different approach by measuring brain network dynamics during an endurance cycling task (Tamburro et al. 2020), showcasing the sensitivity of $E_{glob}$ to shifting physiological demands, as it initially increased during the first stages of cycling but decreased in the last stage as fatigue mounted. Overall, global efficiency appears to be state-dependent, but its modulation under task demands is not consistent across studies.

Another interpretation is that potentially meaningful condition-associated effects did occur within individual trajectories, but owing to their opposing directions, these changes lost a good amount of magnitude once averaged across the group. These divergences are illustrated in the estimated marginal mean plots (Figure 5.2).

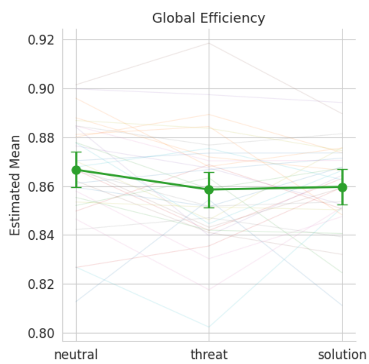



Figure 5.2: EMM for normalised global efficiency. Faint lines trace individual trajectories. For all metrics see Figures 4.2a and 4.2b.

The rationale for examining the effect of climate-related statement frames on global network measures stemmed from theorising cognition as an agent-environment coupling. In the present experiment, understanding of the text was considered to be jointly shaped by the characteristics of text, as well as those of the subject. Access to the subject, evidently, was limited to her brain activity patterns. Individual variation was expected, but the group analysis design was employed to test whether consistent trends in how the brain's functional network configuration shifts in response to different communicative frames exist across individuals. Some degree of group convergence was anticipated given that all participants lived in the same city, spoke German, and had volunteered to take part in the study, allowing for the expectation of overlapping exposure to news media and in some ways a similar sociocultural context. This would have been in line with a view of Climate Change as a *socially concretised object*, enacted through shared linguistic and social practices (Di Paolo, Cuffari et al. 2018). Just as language thematises the body, it also enacts affect (Colombetti 2014). Of course, understanding of the text is an outcome of the dynamic interplay between linguistic structure, situational context *and* individual histories.

The question guiding the analysis was whether shifts in affectively salient communicative frames are to some extent reflected in shared shifts at the neural level[8]; functional network dynamics here wer understood as expressions of an autonomous, adaptive, and self-organising system. While the chosen linear mixed-effects model, with subject as a random intercept, captures stable between-subject differences in overall graph metric levels (general tendencies relative to the group mean), it remains limited to the predefined analysis windows and does not account for the brain activity outside these segments[9]. CAPs, in contrast, were derived from concatenated frames across all runs and participants, including both task and rest data, and thus better align with the notion of functional networks as continuously evolving self-organising systems. However, this increased temporal inclusivity comes at the cost of abstraction, as states are generalised to a level at which finer-grained temporal structure is lost, motivating the complementary use of both approaches.

[8] in broader relevance terms, the test was for the mass media neural effect, not individual reading

[9] An addition of a random slope would allow for variation in both the magnitude and direction of the measure. While it would not have solved the cancelling-out problem, it would have made it more visible. A random slope was not included due to the limited sample size.

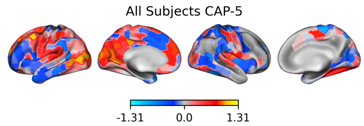



Figure 5.3: CAP5 Surface Plot.

### 5.2.2 *CAPs: Tentative Embodiments*

The stand-out finding from the CAP analysis was a higher count of CAP5 during the solution condition relative to threat. Based on its Yeo-7 (Yeo et al. 2011) cosine similarity profile (Fig.5.4), CAP5 is characterised by strong expression of the somatomotor network, weaker involvement of the ventral attention network, and concurrent deactivation of control and default mode networks. Using the Yeo-17 profile (Fig.5.5) for further differentiation, somatomotor network B shows slightly higher expression than network A, whereas control regions are more strongly deactivated in B, and default mode regions more strongly deactivated in A than B.

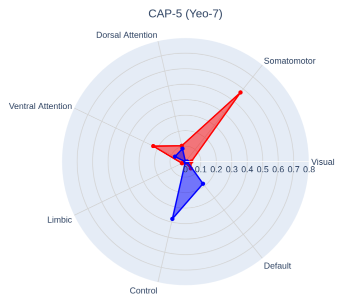



Figure 5.4: CAP5 Yeo-7 cosine similarity profile.

In very general terms, the somatomotor network is said to be responsible for sensory processing and motor coordination. However, as with most networks (Pessoa et al. 2022), recent research hints at a more complicated story that goes beyond a distinct singular function. There is strong evidence that part of the somatomotor system, particularly inter-effector regions of the motor cortex, supports action planning, goal maintenance and integration of bodily states, leading to the proposal of somatomotor-cognitive action network (SCAN) (Gordon et al. 2023).

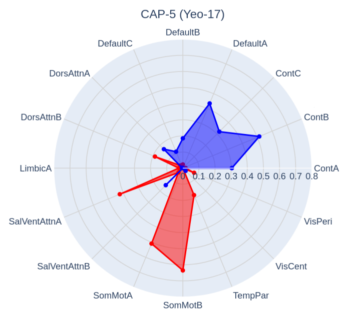



Figure 5.5: CAP5 Yeo-17 cosine similarity profile.

Areas typically involved in action planning and execution have also been reported to be active while observing actions performed by others (Avenanti et al. 2007), as well as while moving things "mentally" (Doganci et al. 2023), showcasing how actions of mental and motor kind are at least partially subserved by common neural systems. Along these lines, a CAP study (D. D. Smith et al. 2025)[10] investigating differences between active and passive learning, after finding increased persistence of CAP with elevated somatomotor network activation on physics task performance, interpreted it as evidence of embodied learning. Extending this to the present study's CAP5–somatomotor network association, alongside concurrent suppression of default and control networks, it could be argued that solution-oriented news may shift readers away from internally focused rumination toward a more externally oriented state of action-readiness[11].

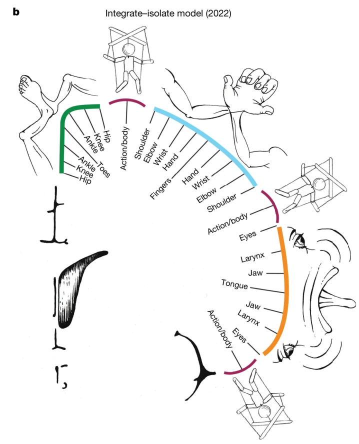



Figure 5.6: Integrate-Isolate Model of Action and motor control proposed by Gordon et al. (ibid.).

[10] The Neurocaps, an open-source Python package developed for this study, is the same package used in the present study.

[11] In this case action is meant in more general folk psychology terms of goal-oriented behaviour.

The solution-oriented statements presented during the experiment are not written as imperatives. None of them emphasise an individual action required to be undertaken. Solution statements for the most part describe possible solutions or alternatives, ongoing efforts, or collective actions aimed at mitigating the climate crisis-related issues. In this particular case then, somatomotor network associations transcend the limits of one's body to collective action—what could be termed "body social". In line with an enactive account of cognition, where language is taken to thematise the body, CAP5's close characterisation with somatomotor activity can be considered as a tentative neural indication of body extended over time and subjectivity. This is not to be directly equated with collective action. Rather, it could be said to capture a normative centre situated outside of the individual body. As argued before, individuals are embedded in linguistic-social networks, and the norms emerging from this networked individuation extend beyond the boundaries of the organic body (Di Paolo, Cuffari et al. 2018). Climate Change as a socially concretised object is one such concern. In this sense, the shift at the neural level may be read as expanded adaptivity: the self-organising system reorganising in relation to norms that arise beyond its boundary to that of the body social.

But. Interpretation is not a conclusion, and one encounters more than a few caveats in between. First, CAPs are abstracted states and higher count and temporal fraction of CAP5 with high cosine similarity to somatomotor network is not equivalent to the latter's dynamics. The emphasis here is on resemblance, not identity. Further, boundaries between CAP-derived states are only moderately stable (see Jaccard Stability 4.6b). This also ties to the fact that statement exposure windows were relatively short, introducing a restricted number of frames per condition and subsequent vulnerability to noise[12].

[12] In particular jeopardising the reliability of fractional occupancy and dwell time estimates, which are inherently dependent on sufficient frame sampling to be interpretable.

Brain network dynamics are messy, and as argued by Pessoa (2018), functional brain networks lack clear boundaries or functional distinctions. Some of the limitations noted above are therefore also reflections of a distributed network profile that inherently resists clean assignment and interpretation. In other words, while harder to interpret, CAP-state data might be closer to how functional networks actually operate. As illustrated in his network model of emotion (Pessoa 2017), affective states emerge from the coordination of interacting large-scale systems. Thus, when we consider CAP5, it is a state dominated by the somatomotor network but also carrying weaker involvement of the ventral attention network alongside concurrent deactivation of control and default mode networks—and its interpretation may not be available by characterising it in reference to resting state network boundaries [13]. The meaning of such a state is not fully given by its spatial profile, but remains bound to the task context in which it unfolded. Following this line, CAP5 is the state whose occurrence distinguishes CAP temporal dynamics in solution versus threat conditions.

[13] One of the results that did not survive FDR correction was a lower count and temporal fraction of CAP3 for the solution condition relative to neutral. Based on its cosine similarity profile, CAP3 is characterised by relatively stronger expression in the default mode and ventral attention networks, with weaker involvement of control and somatomotor networks, alongside concurrent deactivation of visual and dorsal attention networks, suggesting an internally oriented monitoring state. The lower occurrence of CAP3 during the solution condition thus coheres with the CAP5 finding, implying a shift away from evaluative or self-referential processing.

**Note of Caution on CAP Metric Interpretation**

Co-activation pattern (CAP) analysis was initially developed to investigate transient patterns of activity within spontaneous brain dynamics during resting state (Liu and Duyn 2013). It offered an alternative way of characterizing resting-state activity by focusing on temporally discrete co-activation events rather than temporally averaged connectivity estimates. In recent years, the approach has also been adopted to investigate task-based data in order to analyse temporal state dynamics underlying cognitive processes (Freitas et al. 2020; Hasanzadeh et al. 2025; D. D. Smith et al. 2025; Yan et al. 2022). However, the interpretation of CAP metrics appears to remain an open question.

For example, Hasanzadeh et al. (2025) investigated CAP dynamics across three reasoning tasks—Paper Folding, Matrix Reasoning, and Letter Sets—and remained relatively succinct in their discussion of the broader functional relevance of the identified CAP networks. In contrast, D. D. Smith et al. (2025) devoted greater attention to exploring potential functional interpretations through the use of intrinsic functional cosine similarity measures associated with the identified patterns. This discrepancy can be understood in light of the fact that, despite growing empirical use, the interpretation of CAPs remains theoretically underspecified, and it is often unclear to what extent identified patterns reflect discrete functional states, transient coordination tendencies, or statistical properties of the underlying signal structure (Matsui et al. 2022).

### 5.2.3 *Bringing it Together*

According to the enactive account of cognition, understanding of the climate statements unfolds through the interaction between text, bodily history, and ongoing neural dynamics. From this perspective, communicative frames are not expected to produce fixed or uniform cognitive-affective responses, even when examined through functional brain network reconfigurations. Graph theoretical and CAP metrics therefore capture complementary but partial aspects of this process: graph metrics summarise broad structural tendencies of network organisation, while CAPs reflect transient dynamics unfolding within those constraints.

When the findings are brought together, the emerging picture is one of two contrasts: an integration contrast between neutral and explicitly climate-related conditions, and a temporal contrast between threat- and solution-oriented framing. The significant global efficiency and CAP5 findings do not converge on a single neural signature of communicative framing, nor on one unified interpretative account. Given the complexity of the texts and the wide range of individual commitment and engagement, a clear pattern at the brain-wide scale was unlikely from the outset. This is why the study was presented as an explorative one.

The graph-theoretical and CAP analyses appear to capture two distinct adaptive signatures—traces of differently organised engagements with the text. The findings thus do not point to uniform, frame-specific cognitive-affective states, but to ongoing and variable reorganisations of functional brain networks during sense-making. What the evidence foregrounds is the individual variability in how participants engaged with the climate statements, and the capacity of language to thematise the body and to recentre normativity beyond its organic boundaries.

## *5.3 Future Directions*

The current experiment was part of a larger REASON study. The conception of the analysis pipeline came after the experiment was designed. My research questions were thus derived from what was available in the data, and did not guide how data was collected. The analysis by and large was an exploratory one, without testing one specific hypothesis. Research lines were informed by my theoretical interest in the process of sense-making, and the aim to investigate it on the level of large-scale brain dynamics. Methodological choices were made to align with this aim, however, they were also guided by feasibility and practical considerations, including my skills as a researcher, which often led to compromises and trade-offs. Thus, in closing this section, I would like to directly reflect on these limitations and how they could be addressed in future research lines to further explore tentative but generative findings.

### *5.3.1 More Text: Length and Content*

In the current experiment, participants were exposed to climate statements in relatively short time windows. This design choice was made to capture immediate neural responses to different communicative frames, but it also introduced limitations in terms of the depth of engagement and introduction of noise. Following this, short exposure times may not have been sufficient to elicit robust data and to reliably characterise neural patterns. Future studies could explore longer texts and exposure times, or even videos, facilitating sustained engagement. Longer frames would also allow for the use of other dynamic approaches, like sliding window analysis or hidden Markov models, giving more confidence in rejecting the possibility that findings are method specific.

Further, all statements in the present study were climate-related. To be able to claim that observed CAP5 dynamics during solution frames indeed are indicative of socially thematised body, this requires similar observation under socially oriented discourse themes. Current solution frames were a mix of solutions currently undertaken and those that are available but still require action, suggesting different forms of agency. Explicit comparisons between first-person singular, first-person plural, and third-person solution framings could be particularly informative for analysing how linguistic perspective shapes sense-making and extended normativity.

### 5.3.2 Unexplored Data: Resting State and Individual Sentiment

The current dataset contains unexplored and valuable data that could be probed to further explore the observed large-scale brain organisation patterns. Among the most promising avenues are the two resting-state runs, obtained before and after the task. I shifted my analysis towards task runs guided by my interest to explore differences between frame conditions. However, resting state data could be used to investigate how task-related dynamics relate to individual dynamics at rest, which could help to differentiate between trait-like and condition-dependent neural patterns.

I have suggested that divergences of individual trajectories in condition-dependent graph metrics may be indicative of subject-specific ways of engaging with communicative frames, aligned with the enactive proposal of constitutive meaning-making. Besides including resting-state runs, one could utilise questionnaire data regarding personal attitudes towards climate change and SAM ratings, to investigate whether neural dynamics are associated with care and thought given to the issue and reported salience of the texts.

### 5.3.3 Building Bridges: From Theory to Formal Models

In concluding remarks after introducing his network level of emotion (see Section 2.3.3), Pessoa (2017, p. 369) asks: “Can the type of architecture described here be investigated without formal/mathematical tools?”. It is the same question I am asking myself in bringing this thesis to its conclusion.

Enactivism can be compatible with mathematical and computational approaches (Villalobos and Dewhurst 2017). Weinstein et al. (2022) have even developed an enactivist-inspired mathematical framework to talk about cognitive systems. Formalisation will not solve the problem of interpretation or of the access to the underlying process. But if one is to use numerical measures, it becomes important to situate them within a framework that makes explicit how they relate to the underlying processes of interest. Without such a framework, there is a risk that equally rich theoretical and quantitative descriptions are left with a leap of faith interpretation. The lack of a more explicit bridge between theory and quantitative methods for me is the biggest limitation of this thesis. More substantive math knowledge is needed to pursue it further, and I take it as a personal future challenge.

# 6 Conclusion

VLADIMIR: I don't understand.
ESTRAGON: Use your intelligence, can't you?
*Vladimir uses his intelligence.*
VLADIMIR: *(finally).* I remain in the dark.

—Beckett 1954, p.12

This thesis was written with the intention of treating an empirical study within an enactivist-inspired framework. The presented view of cognition was that of a relational process on both theoretical and methodological levels. The project was organised around BOLD data from an fMRI study, in which participants were exposed to climate-related statements framed as either solution-oriented, threat-oriented, or neutral. Enactivism as a *philosophy of nature*, was introduced as a framework for approaching cognition as a process of sense-making that emerges through the ongoing coupling between agent and environment, cutting across biological, social, and historical dimensions.

The brain in this case was treated as an autonomous and adaptive system of systems, whose self-organisation was hypothesised to reflect a broader process of sense-making, without being reduced to its sole locus. In the methodology, this translated into the choice of analytical tools that privilege relational, systems-level, and dynamic descriptions of large-scale brain network configurations, primarily graph-theoretical and co-activation pattern analyses. Taken together, enactivist and network neuroscience tools were employed to explore how text-based sense-making manifests on the level of functional brain network configurations.

Regarding empirical results, graph analysis revealed lower global efficiency for climate-related threat and solution-oriented statements relative to neutral condition, suggesting reduced large-scale network integration when engaging with statements that, on average, participant rated as more negative in valence and more arousing than their neutral counterparts. CAP analysis, on the other hand, showed higher occurrence of CAP5—characterised by strong expression of the somatomotor network, weaker involvement of the ventral attention network, and concurrent deactivation of control and default mode networks—during exposure to solution statements compared to threat framing, tentatively reflecting a shift toward broadly conceived 'action-readiness' state when the texts referred to collective and goal-oriented undertakings. Prior to accounting for the statistical caveat of testing for multiple effects, several other trends were observed, including condition-dependent effects for CAP2 and CAP3; however, none of the latter survived FDR correction. Further, the clustering trends proved non-robust to null model normalisation, suggesting degree-driven rather than condition-specific network changes.

This study has limitations, which are addressed in their respective sections throughout the thesis. The primary tension, however, lies between enactivism as a process-oriented philosophy and the fact that network neuroscience, even when tracing dynamics, requires discretisation at multiple stages: temporal segmentation, spatial parcellation, thresholding, and binarisation. Some of these problems can be mitigated with more sophisticated analysis tools and strategies, but others are inherent to the distance between cognition conceived as a constitutive act and the level at which an empirical study can probe and obtain values. As argued before, this is why theorising is so necessary to engage with empirics.

Theory provides a temporarily stable conceptual space in which empirical findings can be made intelligible and discussed beyond their statistical significance. In this study, due to the exploratory design, the statistically significant findings are tentative, and, as the simultaneous application of graph-theoretical and CAP analyses shows, the interpretative integration of their respective results is not frictionless. In this study, the drawn theoretical plane allows us to consider, during the threat condition reduced global efficiency as a sign of an affect evoked by an affectively salient concept and the prevalence of CAP5 during the solution condition as a potential neural signature of the body extended over time and subjectivity. Both support the view of *Climate Change* as a *socially concretised object*—culturally enacted practice, brought forth through language, media, political discourse. The enactivist and network neuroscience theories also raise a note of caution regarding such interpretation, emphasising that derived graphs and CAP states are mathematical abstractions whose correspondence to ongoing neural dynamics is a matter of ongoing debate.

One contribution from this study to that debate is that group-level statistics likely obscure individually meaningful variation. The considerable inter-individual variability observed in the magnitude and direction of condition-related changes in graph and temporal metrics points to heterogeneous network responses across participants. From an enactivist point of view, that is an expected trend. As argued before, textual sense-making depends on both the text and the reader. The actual frame underlying understanding of the text is always a blend of the communicative frame and the reader's history and ongoing cognitive-affective state, of which neural is a part of. Individual variability, in this case, is not noise to be controlled but a theoretically informative feature of empirical data. Future work attempting to capture the process of contextual engagement, be it with text or other modalities, would benefit less from larger samples that average out this variability and more from methods and analysis strategies that can hold and meaningfully trace those individual trajectories.

# *A Note on Generative AI Use*

This work has been produced using the assistance of generative AI tools. `Consensus` was employed during literature search phase to find topic-relevant articles. `Claude` and `ChatGPT` models were used in developing and and debugging the analysis code. The same models were also used throughout the writing process. On different occasions they were prompted to both, provide feedback, and help in improving the clarity and academic precision of the written text. They were also used more loosely to explore sporadic ideas and identifying potential connections among them.

The research, arguments and the form in which they are presented remain responsibility of the author.

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