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A Comprehensive Exploration of Predictive Processing: An fMRI Meta-Analytic Approach to Investigate "Predictive" Networks Across Multiple Cognitive Domains

Including the Development of a New Tool for the Evaluation of Risk of Bias in Cognitive Studies

Supervisor
Prof. Cristina SCARPAZZA, PhD

Candidate: Camilla FRANGI
Student ID number: 2034628

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Abstract

This work further explores the existence of a network specifically devoted to prediction in the brain. Building on previous knowledge, multiple meta-analyses on General Prediction, Prediction Encoding and Prediction Violation are performed, both within and across different cognitive domains (Cognitive Control, Attention, Language, Motor, and Social Cognition). Domain-specific prediction appears to be mediated by different brain regions depending on the considered domain, which closely resemble those that are involved in signal processing and elaboration in that domain. Moreover, the processing of prediction violation seems to involve the insula and the inferior frontal gyrus, as previous meta-analytic work suggested. Finally, previous findings on the existence of a prediction network in the brain are partially replicated, once again highlighting the role of the insula and the inferior frontal gyrus in said network. Due to unforeseeable computational limitations, these results can be considered only partial and need replication.

In parallel with this meta-analytic work, a new tool for the evaluation of risk of bias in cognitive studies is developed, as the literature lacks such an instrument. This tool is therefore created by adapting a checklist for the assessment of quality in cognitive studies and then applied to a subset of papers from the Social Cognition meta-analyses. Its statistical properties are assessed starting from these preliminary data: although its inter-rater reliability is not good, this instrument shows potential to be widely used in research, once a few adjustments to its structure are made.

Keywords: Prediction; Predictive coding; Meta-analysis, Risk of bias; Neuroimaging.

Contents

Chapter 1

Introduction

How does the brain work? Is there some overarching principle that regulates everything that happens inside a human's head? These and many other questions on the nature of the human brain do not have a definite answer yet, despite many different attempts at an answer have been made. In this work, one of such attempts, predictive processing, will be presented and analyzed, and new evidence for how it may be implemented in the brain will be brought forward.

During the groundwork for this study, a lack of tools for the evaluation of risk of bias in cognitive studies emerged in the literature, which laid the foundations for an effort to design such an instrument. This led to the development of the AEROBICS (Analysis & Evaluation of Risk Of Bias In Cognitive Studies).

1.1   Predictive processing

Predictive processing (also known as predictive coding) is a theory that describes brain function starting from computational models of prediction (Friston, 2002). In this theoretical proposal the brain is considered as a prediction machine, which generates top-down predictions about the input it receives and then corrects them by comparing them to the actual input (Clark, 2013; Friston, 2002). At the beginning, this theory was only applied to perception (Friston, 2002), but then it was extended to include action as well, in what is known as active inference (Adams et al., 2013). Predictive processing is biologically plausible, as it adapts very well to current knowledge about cortical hierarchies and intrinsic connections in cortical areas (Friston, 2002; Friston and Kiebel, 2009).

In the next sections a more thorough description of predictive coding will be provided, in order to allow a better understanding of the work which will be later presented.

1.1.1   A brief history of predictive coding

The intuition about the brain being an inference machine goes a long way back in time: at the very beginning of scientific psychology Helmholtz described perception as an inferential process (V. Helmholtz, 1867, 1971). The revolutionary idea here is that the only data available to sensory

systems are the effects the world has on sensory organs, and from this they have to infer what caused such effects (Clark, 2013). As time went on, Helmholtz's ideas were further developed in different ways (for a brief review see Clark, 2013), but not all of them were relevant for the development of predictive coding.

After the description of the visual cortical hierarchy in the macaque brain (Felleman and Van Essen, 1991), Mumford (1992) developed a model of visual perception based on the hierarchical organization of the cortex: cortico-cortical loops are described as template-residuals loops, which are extremely similar to the basic mechanism behind predictive coding. On the one hand, high hierarchical levels contain templates, which allow the system to make hypotheses about the incoming data. These hypotheses are transmitted to lower areas via descending connections. Lower hierarchical levels, on the other hand, code residuals, that is to say data that do not fit the templates, and broadcast them up the hierarchy to allow for better hypotheses (Mumford, 1992).

Starting from Mumford's description of template-residuals loops, the first hierarchical formulation of predictive coding was provided (Rao and Ballard, 1999): predictive coding was used to explain some extra-classical effects in the visual hierarchy (e.g., *endstopping*, the reduction or elimination of the response of a neuron to an optimally oriented line when it extends beyond the receptive field of the considered neuron). In the model by Rao and Ballard (1999) higher cortical levels compute predictions about the state of lower areas, which are projected downwards via descending connections. In lower areas the prediction signal is compared with the actual activity derived from sensory inputs, and the difference between them, known as prediction error, is sent back up the hierarchy to update the prediction via ascending connections. This is a Bayesian belief updating process, in which prior beliefs are updated by prediction errors from lower areas, and constitutes the basic mechanism of predictive coding (Clark, 2013; Friston, 2002, 2005).

The previously described models were then expanded and formalized in a precise theory in numerous papers by Karl Friston (Friston, 2002, 2005, 2009; Friston et al., 2017). In this formalization, this author introduced some innovations that allowed predictive coding to become a much more comprehensive theory (Stephan et al., 2019). First, besides the fundamental concepts of prediction and prediction error, he introduced the concept of precision: precision is the inverse of variance (Friston, 2002) and allows the system to regulate how each component of the predictive model (i.e., predictions and prediction errors) is weighted (Adams et al., 2013; Fletcher and Frith, 2009; Friston, 2009). This enables the system to become context-sensitive (Hohwy, 2020) and thus able to deal with the noise and ambiguity of the many different situations it may face. Second, Friston specified that the message passing described by predictive coding goes on not only between areas, but also within the same brain area, in its different neuronal layers (Friston and Kiebel, 2009). This idea sits well with the structure of cortical columns (Bastos et al., 2012; see later for a more precise description).

Before moving on to describing the precise mechanisms of predictive coding, it is central to provide an explanation of why this theory provides a unifying account of brain activity.

1.1.2 Predictive processing as a unifying account of brain activity

Before explaining why predictive processing may be regarded as a unifying principle of brain activity, it seems useful to quickly address why having a unifying theory of brain activity may serve our understanding of the brain in the first place.

Epistemologically, empirical work should always be accompanied by theoretical elaboration, so that theory can drive and inform research. This is true for any science, but seems particularly relevant for neuroscience as it strives to explain how the brain works (Hohwy, 2007; Shipp, 2016). As a matter of fact, the brain is an extremely complex object and studying it empirically without a general reference framework may become convoluted and, in the long run, nonsensical, as many different findings are piled up but never organized in a coherent framework.

It has been argued that predictive processing can subsume many different theoretical approaches (Friston, 2010), even those that are apparently opposite to it (Hohwy, 2016). Where does this unifying power come from? Predictive coding can be seen as a corollary of the free-energy principle (Friston, 2005, 2009, 2010; Prosser et al., 2018), which states that biological systems resist a natural tendency to disorder, meaning that they maintain their states in a constantly changing environment (Friston, 2010). This can be generalized to the attempt of biological agents to maintain homeostasis and minimize entropy, which in certain frameworks is defined as the average of surprise over time (Friston, 2010). This means that biological organisms try to minimize the surprise associated with their states at any given moment in order to remain homeostatic (Bastos et al., 2012; Prosser et al., 2018). The most immediate way to accomplish this is to minimize prediction error by improving their predictions or by modifying the input with action (Adams et al., 2013; Bastos et al., 2012; Friston, 2010; see later for a more thorough discussion).

This unifying power can be taken to the extreme, as some interpretations of the minimization of prediction error lead to the conclusion that sensory input is the only evidence an agent can have of their own existence (Hohwy, 2016). In this view, the existence of the agent become self-evidencing, which means that the hypothesis that the agent exists best explains some evidence and thus provides evidence for itself. In summary, evidence supports a self-evidencing hypothesis to the extent the same hypothesis explains that evidence (Hohwy, 2016). It follows that the better the brain gets at seeking out evidence it can explain, the more evidence it has for its own existence (Hohwy, 2016).

Such a point of view may sound appealing or appalling to the reader, but it goes far beyond the scope of what concerns the matter at hand. Here, it is sufficient to point out that the free energy principle, in its different formulations, can explain a number of different phenomena linked to cognition and, in general, to the human mind, thus giving predictive coding the potential to be a unifying principle of brain activity.

1.1.2.1 Perception

As stated before, one could say that predictive coding as a whole started as a way to explain perception (Clark, 2013; Friston, 2002). Perception can be viewed as an inverse problem, as the brain has to infer what caused sensory inputs to describe the reality around itself starting from those inputs alone (Friston, 2002, 2005). A predictive scheme eliminates the ambiguities of solving

such a ill-posed problem (Friston, 2002): without entering into the mathematical formalism, it does not try to infer the causes from the inputs (which leads to an indeterminate answer) but rather to predict the input from a representation of the causes. From the comparison of predictions and actual inputs, a prediction error may be generated and carried back up the hierarchy to optimize the model (Friston, 2009; Shipp, 2016). It is important to remember that this happens on multiple hierarchical levels: each level predicts the activation pattern of the level beneath it and sends prediction errors to the level above (Friston, 2005, 2009; Friston and Kiebel, 2009; Hohwy, 2020). Models based on predictive coding have been proposed for numerous perceptual phenomena, both neural and from subjective perception. In the following list some of the most illustrative ones can be found:

- *Repetition suppression*: repetition suppression is a neural phenomenon in which neurons reduce their firing rate to a specific stimulus when it is presented repeatedly. It can be elicited in both electrophysiological and functional neuroimaging studies (for a review, see Barron et al., 2016). It is clear how repetition suppression can be described by predictive coding: as a stimulus is repeated, its representation becomes more and more accurate, leading to fewer prediction error signals and thus to a reduction of the associated neural signal (Grotheer and Kovács, 2016).

- *Mismatch negativity (MMN)*: the MMN is a negative ERP component which is elicited by any change in a repetitive stream of auditory stimuli (Näätänen, 2003). Such a component can be seen as a transient prediction error, signalling that the model used to predict auditory stimuli up to that point needs to be updated (Friston, 2005).

- *Binocular rivalry*: binocular rivalry is a perceptual phenomenon that rises when the two eyes are presented simultaneously with different visual stimuli. In this case, the subject perceives the two different images distinctively and reports the perceptual alternation of the two (for a review see Leopold and Logothetis, 1999). This phenomenon can be explained by a predictive coding schema (Hohwy et al., 2008): the brain first selects the image most compatible to the model it deems most suitable to describe the world, resulting in the subject perceiving one specific image, even though it is seen by just one eye. This model and its predictions, however, cannot explain away the prediction errors coming from the input from the other eye, which are therefore carried up the hierarchy. To suppress those prediction errors the brain has no alternative but to change its model of the state of the world, switching to the one which describes the visual stimulus presented to the other eye. Therefore, the subject starts perceiving a different image. The change in the model results, nonetheless, in large prediction error signals coming from the input of the first eye, which once again cause the switch in the considered representation. This repetitive process explains the perceptual alternation of the two images (a more thorough description can be found in Hohwy et al., 2008).

1.1.2.2   Action

The free energy principle can be declined to also explain action, in what has been described as active inference (Adams et al., 2013; Friston, 2009, 2010). Active inference could be regarded as an

extension of predictive coding: once again, at any given point in time, the brain is trying to minimize prediction error. This may be achieved in one of two ways (Adams et al., 2013): the brain can either update its predictions to be more similar to sensory input (perceptual inference as described in predictive processing) or change the way it samples the environment so that sensory input corresponds to predictions (action). In the case of action, predictions are transmitted downwards in the motor hierarchy (Friston, 2009, 2010). Crucially, these predictions are proprioceptive in nature, meaning that the brain is trying to predict future bodily states (e.g., muscle tension, position in space; Adams et al., 2013). These descending signals are then compared with the actual proprioceptive input and prediction errors may arise. Again, the key difference between predictive coding and action (as described in active inference) emerges here: in predictive coding prediction errors are explained away as the predictive model is updated, whereas in action proprioceptive prediction errors are automatically transformed into movement. This means that proprioceptive predictions are fulfilled rather than corrected (Adams et al., 2013). This take on action inverts the typical concept of motor control, as fibers descending from the motor cortex do not carry motor commands but proprioceptive predictions. Their comparison with actual proprioceptive input at the level of the spinal cord generates prediction errors, which activate motor neurons, resulting in muscle contraction (Adams et al., 2013). Action, as described in these terms, sits well with the previously cited extreme views on free energy and predictive coding (e.g., Hohwy, 2016): the agent is so dependent on finding evidence for their own existence that they actively look for it by changing their action on the environment.

1.1.2.3 Attention

Predictive coding and, more generally, the free energy principle also provide an innovative way to describe attention (Friston, 2002, 2009). As a matter of fact, attention is conceptualized as precision optimization (Hohwy, 2020), meaning that it regulates the weight that is given to predictions and predictions error when they are compared, becoming the cognitive counterpart of precision (Clark, 2013; Friston, 2002). For example, in a situation for which the agent does not have a strong predictive model, predictions may be weighted less so that prediction errors coming from the input may be stronger and thus cause the updating of the model (i.e., learning) more easily (Clark, 2013). Therefore, attention allows the system to adapt its inferences and learning to a ever-changing world by continuously changing the relative weight given to predictions and prediction errors (Hohwy, 2020). Interestingly, such a view on attention is also relevant for action (Hohwy, 2020): proprioceptive predictions and prediction errors can be differentially weighted depending on the context, which allows the agent to be more adaptive in their environment (Adams et al., 2013; Hohwy, 2020).

1.1.3 Predictive processing in the clinical field

If predictive processing truly is a unifying account of brain activity, it should not only explain how the brain works, but also have the potential to describe what happens when something goes wrong with it (Clark, 2013). This effort to apply predictive coding to the clinical field is ongoing, but has already had some results: most of the research conducted has focused on psychiatric disorders

(Friston, 2023; Smith et al., 2021), but some hypotheses on neurologic disorders have been put forward as well. Crucially, most models of disorders developed from predictive processing rely to some extent on deficits in precision optimization (Friston, 2023). For example, the typical symptoms of Parkinson's disease can be modelled as alterations in the regulation of precision of prediction errors in the motor hierarchy (Adams et al., 2013). In psychiatry, models based on predictive coding have been developed for some psychopathic traits (Prosser et al., 2018), for the positive symptoms of schizophrenia (Fletcher and Frith, 2009) and other psychiatric disorders including depression and autism (for a review, see Smith et al., 2021). For a more comprehensive discussion of the potential of predictive coding in computational psychiatry the interested reader is referred to Friston (2023).

1.1.4 Predictive processing as a biologically plausible account of brain activity

As previously stated, predictive coding is considered a biologically plausible account of brain activity, in the sense that the known laminar organization and anatomical connections in the brain sit well with the way this theory describes message passing within and between areas in brain hierarchies (Bastos et al., 2012; Friston, 2002; Friston and Kiebel, 2009). Interestingly, this applies to the motor system as well (Adams et al., 2013; Bastos et al., 2012). Nonetheless, this biological plausibility is not surprising, as predictive coding was first developed in close connection to empirical evidence on cortical hierarchies (Mumford, 1992; Rao and Ballard, 1999).

1.1.4.1 Forward and backward extrinsic connections

Predictive coding describes each kind of message (i.e., predictions, prediction errors, and precision signals) as being transmitted by different kinds of connections (Friston, 2002, 2005). Forward connections go from a lower to a higher hierarchical level and therefore carry prediction errors. Backward connections start in higher cortical levels and terminate in lower ones, carrying either predictions or precision signals (Friston, 2002, 2005; Friston and Kiebel, 2009). It is important to note that lateral connections, linking areas at the same hierarchical level, exist. This kind of connections are not directly linked to signal transmission but allow the competition between different predictive models, as predicted by the mathematical models describing predictive coding (for a more formal description, see Friston, 2002).

Given that all these are extrinsic connections, they connect different areas of the same hierarchy and are considered to have different effects on the neurons they target. Forward connections are driving and always elicit a response. Backward connections, on the other hand, can be either driving (if they convey predictions) or modulatory, which serves as a demonstration of the fact that they mediate precision optimization (Bastos et al., 2012; Friston, 2005).

These connections also have different laminar origins and targets. Forward extrinsic connections originate from superficial pyramidal cells and terminate in layer IV, whereas backward extrinsic connections start from deep pyramidal cells and end outside of layer IV (Bastos et al., 2012). Clearly, this is a simplification and origins and terminations of fibers may not be so clearly defined. Nonetheless, this distinction is useful to understand the intrinsic connectivity of brain areas.

1.1.4.2 Different neurons for different functions: intrinsic circuitry

As hinted above, predictive coding rises from mathematical modelling of how prediction may happen in the brain (Friston, 2002, 2005). As the development of this theory went on and more equations to describe it were formulated, the message passing dynamic that was suggested by the mathematical formalism led Friston and Kiebel (2009) to hypothesize the existence of the two distinct neuronal populations to code signals as required by predictive coding (i.e., one population coding predictions and the other one coding prediction errors). Evidence for the existence of such populations emerged, as it became evident that superficial and deep layers of the cortex, although deeply interconnected, have different processing functions (Bastos et al., 2012).

Predictive processing posits the existence of four (plus one) kinds of units, based on the combination of two basic properties that define the function of each neuron (Friston and Kiebel, 2009; Shipp, 2016).

- *Error vs. expectation units*: error units receive prediction signals and generate prediction errors. On the contrary, expectation units are responsible for the generation of predictions to be conveyed to lower hierarchical levels (Shipp, 2016).

- *Units for causes vs. for states*: cause units code for the aspects of the environment that produce regularities in sensory input (e.g., visual objects), whereas state units code for the dynamics of reality, meaning the momentary changes in input due to interactions among causes or between a cause and the context (e.g., an object being partly occluded by something else; Shipp, 2016).

The interaction of these properties gives rise to four different kinds of neurons (i.e., error units for causes, error units for states, expectation units for causes, and expectation units for states; Shipp, 2016). The fifth class of neurons are the ones mediating precision and its optimization. They have a modulatory effect on other neuronal units and can be conceptualized as coding the reliability of the signal provided by each unit according to the system.

The dynamics of message passing among these classes of cells are extremely complex and well beyond the scope of this work (a thorough description can be found in Shipp, 2016). Nonetheless, in order to understand how this theoretical circuit maps onto real neural circuitry, some basic hints will be given (Bastos et al., 2012; Shipp, 2016):

- Error units for causes are particularly associated with interactions across levels: they receive prediction signals from higher hierarchical levels and generate prediction errors to update the model at higher levels.

- Message passing between units for states is mostly intrinsic to any given level. Nonetheless, units for states may receive modulatory inputs from neurons coding precision from higher hierarchical levels.

- Error units receive both excitatory and inhibitory inputs from expectation units in the same hierarchical level and the one above to compare signals and compute the error signal.

The identification of these distinct neuronal populations with specific types of neurons known to be differentially present in cortical layers was hypothesized together with the existence of such neuronal distinction (Friston and Kiebel, 2009). Nonetheless, a precise mapping onto the anatomy of microcircuitry and intrinsic connections was first provided by Bastos et al. (2012): the authors start from the description of the canonical microcircuit (which models how information flows in the cortical column; Douglas and Martin, 1991; Douglas et al., 1989) and assign to each neuronal population described there a specific role according to predictive coding, based on the known connections among cellular layers. Shipp (2016) takes another perspective on the link between the canonical microcircuit and the neuronal populations hypothesized from predictive coding, as the canonical microcircuit (Douglas et al., 1989; Douglas and Martin, 1991) and evidence for its existence are analyzed to verify whether they are in accord with predictive coding. The author concludes that there is good correspondence, although at times predictive coding is lacking in describing the richness of cortical organization (Shipp, 2016).

Notably, in this effort to map neuronal populations in the different layers, neurons coding precision have also been considered, together with the biological mechanisms that may mediate precision optimization (Friston et al., 2017; Shipp, 2016). It is general consensus that precision is mediated through neuromodulatory transmitter systems (e.g., by NMDA receptors, which are perfect candidates to have modulatory effects due to their long time-dynamics) or population dynamics (Friston et al., 2017).

Most of the work on the laminar organization of the cortex has been carried out on animal models or simulations (Bastos et al., 2012), but there is potential for in-vivo non-invasive studies of the laminar organization of the brain in humans: the development of laminar functional magnetic resonance imaging (laminar fMRI; e.g., Koopmans et al., 2010; Polimeni et al., 2010) allows for some hypotheses brought forward by predictive coding to be tested in humans and, more generally, makes it possible to compare predictive coding against other theories of brain functioning (Stephan et al., 2019).

1.1.4.3 Predictive processing is evolutionarily plausible

As pointed out in this section, there are a number of reasons for which predictive coding can be deemed biologically plausible. As the last piece of the puzzle, it is important to verify whether it is also evolutionarily plausible. In order to do so, one needs to see whether predictive processing makes organisms more fit to their environment and if there are plausible evolutionary mechanisms that can explain its origin.

It has been argued that brain structures underlying predictive coding are not a late evolutionary addition but rather emerged gradually from simpler predictive loops, already present in early evolutionary ancestors to humans (Pezzulo et al., 2022). These ancient predictive loops originated from even older generative models called homeostats (Pezzulo et al., 2022): as the name suggests, these simple loops were involved in the regulation of homeostasis, by constantly predicting the optimal homeostatic state and thus leading the organism to act to reach said state (in line with the principles of active inference). This kind of processing allows only reactive action once the status of the organism changes from the optimal one. Nonetheless, predictive action (meaning

acting to avoid change from the optimal status) can be achieved with the interaction of different homeostats, which form a so-called allostat (Pezzulo et al., 2022). The elaboration from unimodal homeostats to multimodal allostats is the first mechanism of evolution that could have led to the development of the predictive brain as it has been described up to this point. There are other three mechanisms that have been hypothesized (Pezzulo et al., 2022): the duplication of predictive loops (which enlarges the behavioral repertoire of the organism), the equipment of the model with temporal depth (which allows prospective and retrospective inference), and with hierarchical depth (which results in a loop made of different hierarchical levels that encode latent states unfolding at different timescales). Different combinations of these mechanisms may generate brains of different complexity and predictive capacities, including primate brains (Pezzulo et al., 2022).

1.1.5   Predictive processing and neural networks

As reported earlier in this work, predictive coding took its footing from works on the sensory hierarchies (Mumford, 1992; Rao and Ballard, 1999). It therefore goes without saying that predictive processing represents a good model for perceptual networks in the brain, with most of the work in this theory focusing especially on the visual system (Clark, 2013). The same goes for the motor hierarchy, when the concept of predictive coding is expanded in active inference (Adams et al., 2013; Friston, 2009).

Some efforts have been made to apply predictive coding to other known anatomical and/or functional networks in the brain (Friston et al., 2017). For example, the functional neuroanatomy of cortico–basal ganglia–thalamic loops has been organized into a predictive model, whose message passing according to predictive processing (also in its neuronal components) makes sense with known anatomical connections among these regions (Friston et al., 2017). Another example is an attempt to describe the mirror neuron system (MNS; Rizzolatti and Craighero, 2004): the problem of inferring one's intention and goals from their movements can be conceptualized as being hierarchical in nature, which makes it suitable for the application of predictive coding (Kilner et al., 2007). Once the MNS is described as a predictive system, it becomes evident that a predictive model gives the simplest answer to the question about how mirror neurons do what they do: by taking into account the context, it allows the MNS to infer different intentions from visually identical movements (Kilner et al., 2007). Notably, this predictive hypothesis for the MNS has received some empirical support (Kilner et al., 2007).

From what reported above, it clearly emerges that predictive coding as a general theory of brain functioning allows for the development of plausible domain-specific models of different brain functions and networks. This left researchers wondering whether in the human brain a domain-general prediction network exists, defined as a set of cortical and subcortical regions engaged in higher-level prediction across functional domains and processing modalities (Siman-Tov et al., 2019).

To date, it is possible to identify two attempts at answering this question (Ficco et al., 2021; Siman-Tov et al., 2019). Both of these works used a meta-analytic approach, which allows the combination of large sets of data from different studies to find any underlying regularities and, in the case of functional neuroimaging studies, brain areas that are consistently active across different tasks with different stimuli. The meta-analyses run by Siman-Tov et al. (2019) and Ficco et al.

(2021) will be now described in detail, as they constitute the foundations of the work that will be conducted here.

1.1.5.1 Siman-Tov et al., 2019. *Is there a prediction network? Meta-analytic evidence for a cortical-subcortical network likely subserving prediction.*

This meta-analysis considers 39 functional neuroimaging studies concerning prediction formation and violation in three domains: music, language, and action perception. The analysis was carried out using Activation Likelihood Estimation (ALE; for a description of this method see Eickhoff et al., 2009, 2012). The authors report significant convergence in several cortical and subcortical clusters: bilateral anterior insula, inferior frontal gyrus and ventral premotor cortex, right pre-supplementary motor area, middle frontal gyrus, supramarginal gyrus and subthalamus, left posterior superior temporal sulcus, caudate and cerebellar lobule VII. A contrast analysis comparing prediction violation and formation was run but did not support a major difference between the brain regions mediating these processes.

The authors argue that the reported areas form a network that subserves domain-general higher-level predictive processing. In the discussion, they put forward some hypotheses concerning the connections between the proposed predictive network and other known neural networks, as it shares some hubs with the salience network, the ventral attention network, and the mirror neuron system. Moreover, the proposed network closely resembles the brain regions implicated in implicit learning and social cognition. Notably, all the functions referred here or mediated by the cited networks can be (or have already been) described with models rooted in predictive coding.

1.1.5.2 Ficco et al., 2021. *Disentangling predictive processing in the brain: a meta-analytic study in favour of a predictive network.*

This meta-analysis considers 70 functional neuroimaging studies concerning prediction encoding and violation without selecting any specific domain. The analysis was carried out using Activation Likelihood Estimation (ALE; Eickhoff et al., 2009, 2012). The authors also investigate the connectivity patterns of the areas showing convergence in ALE using the Seed-Voxel Correlations (SVC) Consensus technique (Boes et al., 2015; Darby et al., 2019). In short, this technique highlights the regions whose activity correlates with the one in the regions emerging from ALE.

In this study, the analyses for prediction encoding and violation were carried out separately, then the two datasets were merged to allow for the analysis of general prediction. The results are summed up in the following bullet points for easier reading:

- *Prediction violation*: significant convergence was reported in two clusters, one in the left inferior frontal gyrus and the other in the left anterior insula (with some overlapping with the claustrum).

- *Prediction encoding*: no significant clusters emerged at various thresholds of significance. The analysis was then carried out with an uncorrected threshold. The results of this exploratory analysis will not be reported here, but the interested reader is referred to the original paper (Ficco et al., 2021).

– *General prediction*: significant convergence was reported in clusters spanning in the frontal and parietal lobe, including the left inferior frontal gyrus, the bilateral insula, the right frontal superior frontal gyrus, the bilateral inferior parietal lobules, and the left precuneus.

From the SVC Consensus analysis, the results from the three conditions were extremely similar, therefore the authors report just the ones for general prediction. Peaks are located in the left inferior frontal gyrus, the bilateral superior temporal gyrus, the left thalamus, the left hippocampus and the left cerebellum.

The maps obtained from the ALE and SVC analyses show a high similarity, which suggests that active areas tend to form a coherent functional network. The results obtained in this meta-analysis are reported as evidence for the existence of a prediction network across sensory modalities and a variety of tasks, which overlaps with known large-scale networks for attention and task execution.

The ALE results for Prediction Violation replicate previous findings on the insula and the inferior frontal gyrus only. On the one hand, the convergence in the insula may mean that any prediction violation, regardless of its nature, produces an error broadly related to the self. On the other hand, the inferior frontal gyrus is involved in detecting a mismatch between expectations and decisions, hinting at a role in expectation violation. Moreover, intrinsic connectivity between the insula and the inferior frontal gyrus was predicted by the degree of uncertainty intolerance, which indicates a sensitivity to error signals. The ALE results for general prediction replicate some of the hubs of the networks proposed by Siman-Tov et al. (2019), which extends their findings to more domains than the ones they considered.

As previously reported, the SVC Consensus results are highly similar in all conditions, which is particularly relevant when considering prediction encoding and violation: these findings strongly support that the same network underlies both functions. Moreover, the network obtained in this analysis across conditions resembles very closely the task positive network (TPN), a large-scale brain network involved in task execution. The TPN is usually divided into three branches: the salience network, the ventral attentional network and the dorsal attentional network. Again, this replicates the results of the meta-analysis by Siman-Tov et al. (2019). Interestingly, the network proposed by Ficco et al. (2021) is also negatively correlated with the default mode network (DMN), as the TPN usually is. The authors deem this as surprising, since the DMN was suggested as being responsible for creating and updating internal predictive models. This finding requires further research into it.

1.1.6 All in all, is there a prediction network in the brain?

The work presented in this report starts from the results of the previously described meta-analyses (Ficco et al., 2021; Siman-Tov et al., 2019). It takes after them both methodologically and conceptually. First of all, it is a meta-analysis aiming at the potential discovery of a set of brain regions involved in prediction. The analysis *per se* will not be carried out using ALE here, but it seems important to stress that this work is part of a bigger effort to find new insights into the existence of a prediction network with a variety of methods, including ALE (Costa et al., 2023b).

This meta-analysis will be actually made up of many different meta-analyses. Taking from Ficco et al. (2021), included contrasts will be divided into a Prediction Encoding and a Prediction

Violation dataset, which will be analyzed separately. These datasets will be then pooled together to perform a General Prediction (meaning process-general) meta-analysis. Moreover, taking from Siman-Tov et al. (2019), studies focusing on prediction in some specific cognitive domains will be considered, namely Cognitive Control, Attention, Language, Motor, and Social Cognition. Again, these datasets will be then pooled together to run an Overall (meaning domain-general) meta-analysis.

To summarize, for each cognitive domain considered three different meta-analyses will be conducted (i.e., Prediction Encoding, Prediction Violation and General Prediction). At the end, the same will be done for the domain-general datasets, which will include all the studies from each domain plus some studies on Memory, Music and Pain. These domains were considered for inclusion but did not reach a sufficient number of studies to run a reliable domain-specific meta-analysis. In total, 18 different meta-analyses will be conducted. For ease of reading, from this point forward the meta-analyses will be referred just by the domain and the specific process they investigate (e.g., Attention Encoding, Overall Violation, Language General, and so on).

This work aims at expanding the current knowledge on how prediction works in the brain, both in a domain-specific and in a domain-general manner. First, it tries to clarify whether domain-specific prediction networks (maybe intertwined with a general prediction network) exist. Second, it attempts to further clarify whether Prediction Encoding and Violation are mediated by different areas or they can be considered as different expressions of the same areas (Ficco et al., 2021). Finally, it will try to characterize the already hypothesized prediction network (Ficco et al., 2021; Siman-Tov et al., 2019) more precisely, as it will include a significantly higher number of studies, thus increasing the power of the meta-analysis.

1.2   Risk of bias

When conducting research, one can never be sure if the results they obtained are true or the consequence of some mistake made along the way. This is the reason why researchers try to control every variable that may impact their studies, so that they can be certain, to some degree, of the fact that their findings result from the manipulation they ran.

Bias is a specific kind of error, as it is systematic (Boutron et al., 2019), which means that it is caused by some underlying cause that alters all the results in the same way (e.g., an ill-calibrated scale weighting every object 43 grams more than it actually weights). When it comes to systematic reviews and meta-analyses, the definition of bias gets more complicated, because it can arise from two different sources (Boutron et al., 2019): the actions of the authors of the review/meta-analysis or of the primary authors, meaning those who conducted the included studies.

In this work, the focus will be on the bias in included studies, as a paucity of instruments for its evaluation emerged during the preparation of the previously described meta-analyses. Biases due to the actions of the people conducting the review or meta-analysis can be avoided by adhering to published guidelines for these kinds of studies (e.g., the PRISMA statement; Liberati, 2009; Moher et al., 2010; Page et al., 2021a, 2021b).

Given that it is impossible for review/meta-analysis authors to assess the presence of biases

in the included studies with certainty, it is more appropriate to refer to a result as being at risk of bias (Boutron et al., 2019). Risk of bias can therefore be defined as the likelihood that some features of the study design or of the conduct of researchers will lead to misleading results (Boutron et al., 2019; Moher et al., 2010; Page et al., 2021a). It can be further characterized into two classes (Boutron et al., 2019; Moher et al., 2010; Page et al., 2021a):

- *Risk of bias in results of included studies*: the likelihood of the results of a review/meta-analysis being wrong because of biases present in the included papers.

- *Risk of bias due to missing results*: the likelihood of the results of a review/meta-analysis being wrong because of the absence of studies that should have been included (e.g., because of publication bias, which describes the tendency to publish only significant results, leaving out countless instances of non-significant ones).

The extreme importance of evaluating both of these kinds of biases is stressed in the main guidelines for reviews present in the literature, namely the ones for Cochrane Reviews (which include both systematic reviews and meta-analyses of healthcare studies; Boutron et al., 2019) and the PRISMA Guidelines (developed specifically for systematic reviews and meta-analyses of clinical interventions, but deemed relevant to any systematic review or meta-analysis; Liberati, 2009; Moher et al., 2010; Page et al., 2021a, 2021b).

The instrument developed here focuses on the first kind of risk of bias, as statistical methods to evaluate the risk of bias due to missing results are already available (for a review on methods for the evaluation of non-reporting biases, see Lin et al., 2018).

A brief overview of previously developed measures of risk of bias in results of included studies seems needed before describing the new instrument presented here for the first time. As a matter of fact, the work to develop this innovative measure started from the shortcomings of what was already present in the literature. Please note that, from now on, risk of bias in results of included studies will be referred simply as *risk of bias* to make reading more fluid.

1.2.1 Measures of risk of bias in the literature

Only three relevant instruments for the assessment of risk of bias in reviews and meta-analyses emerged after a thorough search of the scientific literature. All three focus on clinical studies, which *per se* is problematic. The reasons for this will be clarified in a following section of this report.

1.2.1.1 Wells et al., 2000. *The Newcastle-Ottawa Scale (NOS) for Assessing the Quality of Nonrandomized Studies in Meta-Analysis.*

This scale (commonly referred to as just NOS; Wells et al., 2000) assesses the quality (an outdated term used to indicate the inverse of risk of bias, i.e. the higher the quality of a study, the lower the risk its results are biased) of non-randomized clinical studies before they are included in a meta-analysis. Despite its deprecated terminology it is still renowned and used quite extensively (amassing over 18,000 citations on Google Scholar at the time of writing). The NOS is made up of

8 items, which evaluate possible sources of bias, divided into three domains based on which phase of the study they are linked to:

– *Selection*: this domain refers to risk of bias arising from the selection of participants.

– *Comparability*: this domain is useful to ascertain if cases and controls are actually comparable on most factors.

– *Outcome/exposure*: this domain evaluates whether exposure and/or treatment were performed in the same way in controls and cases.

The NOS is definitely an easy-to-use and quick measure for quality/risk of bias, but concerns about its validity have been raised (Stang, 2010). Moreover, as reported by Stang (2010), this scale has never been published in a peer-reviewed journal, casting further doubts on its statistical properties. Although the paper by Stang (2010) is more than 10 years old, to this day the NOS seems to have not been published in any peer-reviewed journal.

1.2.1.2 Tools for the evaluation of risk of bias in Cochrane Reviews

Cochrane Reviews are a gold standard when it comes to reviews and meta-analyses in healthcare, as they have to be written according to a specific manual, the *Cochrane Handbook for Systematic Reviews of Interventions*. The Cochrane Organization provides a number of instruments for the evaluation of risk of bias on a specific website (https://www.riskofbias.info/), but the main ones are two:

– *RoB 2*: it is the updated version of the Cochrane tool for assessing risk of bias in randomised trials (Higgins et al., 2019; Sterne et al., 2019).

– *ROBINS-I (Risk Of Bias In Non-randomised Studies - of Interventions)*: this scale assesses risk of bias in non-randomised trials (Sterne et al., 2016), as the name itself suggests.

Despite their different target studies, these measures have the same general structure, which guides researchers through some precise steps to produce an overall risk-of-bias judgement about every study they want to include in their review/meta-analysis. Each tool screens a number of domains for risk of bias, based on the specific features of the kind of research it is developed for. On the one hand, the RoB 2 (Higgins et al., 2019; Sterne et al., 2019) screens for bias linked to the randomization process, to deviations from intended interventions, to missing outcome data, to the measurement of the outcome, and to the selection of reported results. On the other hand, the ROBINS-I (Sterne et al., 2016) screens for bias linked to confounding, to the selection of participants, to the classification of interventions, to deviations from intended interventions, to missing data, to the measurement of outcomes, and to the selection of reported results. Each domain is screened for bias through the use of the so-called signalling questions: they call for a yes/no answer and allow for a somewhat structured assessment of risk of bias. Based on the answers to these questions, authors can provide a risk-of-bias judgement for each domain and afterwards an overall risk-of-bias judgement, which again describes the risk that including that particular study in the review/meta-analysis being carried out will introduce some bias in the results due to the

likely presence of bias in the results of the study itself. Both these instruments also have optional components to evaluate the direction of bias in every domain and overall.

The RoB 2 (Higgins et al., 2019; Sterne et al., 2019) and the ROBINS-I (Sterne et al., 2016) show some differences as well, also given that the RoB 2 has been updated more recently. For example, the possible risk-of-bias judgments are different for the two measures: in the RoB 2 the risk of bias may be judged as low, raising some concerns, or high, whereas in the ROBINS-I it may be determined to be low, moderate, serious, or critical.

These tools rely heavily on the expertise of the researcher and might be therefore challenging to use for someone approaching the field of systematic reviews and meta-analyses for the first time. This dependence from the rater's expertise is well recognized by the authors (Higgins et al., 2019; Sterne et al., 2016, 2019) but is considered inevitable, as some degree of subjectivity in the evaluation of single papers cannot be avoided. Another problem that has been reported in the use of the ROBINS-I (which probably applies by extension to the RoB 2 as well; Igelström et al., 2021) is the misapplication of this tool: researchers are sometimes too confident of their own expertise and make unjustified modifications to the ROBINS-I protocol, thus making it less effective in detecting overall risk of bias. Often the report of risk-of-bias assessment is also lacking (Igelström et al., 2021), in the sense that many reviews applying the tool do not refer to its use in their reporting of results. Finally, it is sometimes the case that the results obtained in the evaluation of risk of bias are not used, meaning that studies rated at high risk of bias are included in the analyses anyway (Igelström et al., 2021). All these problems are more serious for reviews of low methodological quality (Igelström et al., 2021).

1.2.2 Why a new tool to measure risk of bias?

As previously reported, the need of a new tool to evaluate risk of bias emerged in the preparation of the meta-analyses on predictive processing which will be later described.

Considering the guidelines for reporting a neuroimaging meta-analysis, namely the PRISMA Guidelines in their 2020 update (Page et al., 2021a, 2021b), a thorough analysis of risk of bias in the included studies seemed vital. Upon searching the literature, however, the results were inadequate: the available tools, even the well-developed and peer-reviewed ones (i.e., the RoB 2 and ROBINS-I), are specifically designed for reviews and/or meta-analyses of clinical trials. Applying them to evaluate risk of bias in a meta-analysis of a totally different kind of study would not be feasible, as potential sources of bias change with the nature of the study itself. For example, deviations from intended interventions would not be a problem at all for a neuroimaging study run on healthy participants, as there is no intervention to deviate from in the first place.

Starting from this, the decision to develop a new tool for the evaluation of risk of bias in cognitive studies was made and the AEROBICS (Analysis & Evaluation of Risk Of Bias In Cognitive Studies) was created. For a detailed description of the process that led to the conception and development of the AEROBICS, see the section *Evaluation of risk of bias* in the chapter *Materials and methods*.

Chapter 2

Materials and methods

All steps of this study are in line with the PRISMA Guidelines (Page et al., 2021a,b).

2.1 Literature search

The literature search was systematically conducted on three different databases, namely PubMed (https://pubmed.ncbi.nlm.nih.gov/), Embase (https://www.embase.com/), and PsycInfo (ProQuest; https://www.apa.org/pubs/databases/psycinfo). The research strings and the number of papers obtained with each search is available in Appendix A. The total number of papers found was 4,873.

The literature search included studies published until May 30, 2022.

2.2 Study selection

Given the large amount of relevant papers, selecting only those actually pertaining to the research question being investigated was of key importance. A number of inclusion and exclusion criteria were therefore implemented, starting from the research question and current guidelines for meta-analyses of neuroimaging studies (Müller et al., 2018).

To be included studies should:

- Investigate prediction, either when it is violated or when it is encoded. A number of different terms describing prediction were included in the search strings (e.g., expectancy, anticipation).

- Use functional neuroimaging, either functional Magnetic Resonance Imaging (fMRI) or Positron Emission Tomography (PET).

- Include healthy adults only.

- Include at least 5 participants.

- Report results in a standardized coordinate space (either MNI or Talairach).

- Use data from the whole brain.

– Report contrasts coded so that activation in the *prediction* condition would be higher than in the *control* condition.

– Use a univariate approach to data analysis, which reveals localized increased activations.

Experiments were excluded if:

– They used techniques other than functional neuroimaging. In the search strings a number of methods were explicitly excluded: Diffusion Tensor Imaging (DTI), machine learning, structural MRI, neurostimulation techniques (transcranial Direct Current Stimulation, tDCS; Transcranial Magnetic Stimulation, TMS), and electrophysiological techniques (electroencephalography, EEG; intracranial electroencephalography).

– Their samples included patients (especially ones with neurodegenerative disorders) and/or children.

– They were single-case studies, animal studies, reviews, meta-analyses, clinical trials, or longitudinal studies.

– They included Region-Of-Interest (ROI) or Small Volume Correction (SVC) approaches.

After deleting duplicates and screening the abstracts of the articles found in the initial search, the total number of eligible papers whose full text was read was 409.

The remaining articles were assessed for eligibility and after a double-check, coordinates from 252 experiments were included in the Overall General meta-analysis. In the Overall Encoding and Overall Violation meta-analyses 134 and 175 experiments were included, respectively. The same experiment could provide data for both the Encoding and the Violation condition, depending on how its contrasts were coded. For papers describing more than one study, the single experiments have been considered as separate data entries.

Please note that this selection process described here is the one for the Overall General meta-analysis. Selected experiments were then assigned to one or more specific domains and conditions based on the contrasts they contained and the phenomena they investigated.

Appendix B contains a table with the number of papers included in each meta-analysis, the PRISMA flow diagram (Page et al., 2021a) describing the process of article selection, and a comprehensive list of all the papers included in all meta-analyses.

2.3   Data extraction

Once the eligible studies were identified, data extraction was performed. The following information was extracted: the coordinates of significantly active foci in the contrasts of interest, their significance values (either t-, z-, F-, or p-values, depending on what was provided in the paper), and the number of participants.

2.4 Evaluation of risk of bias

As previously stated, the evaluation of risk of bias is considered a key point for reviews and meta-analyses in most guidelines (Page et al., 2021a; Page et al., 2021b), including those specific for reviews and meta-analyses of neuroimaging studies (e.g., Müller et al., 2018). To evaluate risk of bias the AEROBICS (Analysis & Evaluation of Risk Of Bias In Cognitive Studies) was used.

This tool was developed starting from the PECANS (Preferred Evaluation of Cognitive And Neuropsychological Studies) Checklist (Costa et al., 2023a), which is a newly developed checklist to evaluate the quality of methodology and reporting in cognitive and neuropsychological studies. It was developed by a Delphi panel of experts and it is thought to provide a quick and easily applicable way to improve papers before publication and evaluate them afterwards. It is divided into sections which are based on the usual sections of a scientific paper. The scope of this checklist, however, is much broader than the evaluation of risk of bias, therefore, after a thorough analysis of all the items of the PECANS, only those relevant to risk of bias were selected. After selection, items were grouped in four domains, which describe the possible areas in which bias may arise in cognitive studies, namely participant selection, experimental task, support scales, and statistics. Items were also rephrased to fit with the scoring system used by the AEROBICS, as it is different from the one used by the PECANS, in that it does not call for yes/no answers. The user is instead called to judge the risk of bias linked to every statement of the AEROBICS (choosing among *low, raising some concerns, moderate,* and *high*, mimicking the scoring system used in Cochrane tool for risk-of-bias evaluation; Higgins et al., 2019; Sterne et al., 2016, 2019). After having completed the judgments for all the items, the user is guided in producing a risk-of-bias judgment for each domain and then for the whole study.

The protocol for the AEROBICS can be found in Appendix C.

In this work, the AEROBICS was used only on a subset of the studies from the Social Cognition domain, due to time constraints. Two independent raters evaluated risk of bias and then the inter-rater reliability of the tool was calculated using R Statistical Software (v4.3.1, https://www.R-project.org/; R Core Team, 2023) in RStudio (v2023.6.2.561, http://www.posit.co/; Posit team, 2023) with package *irr* (v0.84.1, https://cran.r-project.org/package=irr; Gamer et al., 2019).

2.5 Meta-analyses protocol

All meta-analyses were carried out using Seed-based d Mapping with Permutation of Subject Images (SDM-PSI, v6.22, https://www.sdmproject.com/; Albajes-Eizagirre et al., 2019a, 2019b). Before starting the actual analyses, it is necessary to prepare the input files for the software. In particular, for each experiment the software needs to be fed the sample size, the software and set of standard coordinates (either MNI or Talairach) used in data analysis, the coordinates of significantly active foci, and the t-value associated with each one of the them. For experiments using any indicator of significance other than t-values, the online utilities provided by the developers of SDM-PSI (https://www.sdmproject.com/utilities/) were used to convert them into t-values.

The algorithm used by SDM-PSI is based on effect sizes found in experiments. In the first step, it is necessary to select the cluster peaks (and statistical maps, if available) according to the

inclusion criteria of the meta-analysis. It is important to check whether the same threshold value was applied to the whole brain; in case different thresholds are used, the developers provide a guide on how to select which values to use (Albajes-Eizagirre et al., 2019a). After the software is fed these pieces of information (together with those previously indicated), it estimates from the t-values the lower and upper bounds of possible effect size images. Afterwards, SDM uses MetaNSUE (a meta-analytic method that allows an unbiased inclusion of studies with Non-statistically Significant Unreported Effects by using maximum likelihood estimation and multiple imputation techniques) to estimate the most likely effect size and standard error and executes multiple imputations to add noise to the estimations within the previously established bounds. SDM-PSI then performs a meta-analysis on each imputed dataset and combines the imputed meta-analyzed datasets with Rubin's rules. Finally subject images are recreated to run standard permutations tests, in which the distribution of maxima is used to correct for multiple comparisons. In particular, SDM uses Family-Wise Error (FWE) Rate to correct for multiple comparisons.

Every meta-analysis included in this work was conducted as follows:

1. Data were preprocessed using the native preprocessing function of SDM-PSI.

2. The actual meta-analysis was conducted with the method described above.

3. The results were corrected for multiple comparisons using FWE and 1,000 permutations.

4. The corrected results were thresholded to identify significant clusters, with an extent threshold of 100 voxels.

5. A mask was created for every significantly active cluster using the MNI coordinates provided at thresholding.

6. The mask was used to extract the statistics linked to that specific cluster, namely: Hedges' g (an indicator of effect size, with its estimated value, variance and SDM-Z value), H^2 and I^2 (two different measures of between-study heterogeneity). Only I^2 will be interpreted in depth, as it is more intuitive to comprehend: it represents the variance explained by study heterogeneity in the results (Higgins and Thompson, 2002).

7. Finally, the extracted effects sizes were tested for biases, in particular for publication bias, with Excess Significance tests and funnel plots.

Chapter 3

Results

3.1 Meta-analyses on predictive processing

In each subsection, the results of the three meta-analyses for that specific domain are reported. For each meta-analysis, the main results are presented in the text and are completed by a table, containing the number of the cluster (under column Cl), the MNI coordinates of its main peak, the values of the statistics described in the previous chapter and the results of the Excess Significance test. A figure illustrating the clusters of significant activation for each meta-analysis is also presented.

Please note that the null hypothesis of the Excess Significance test is the absence of publication bias, therefore failing to reject it is the most desirable result. Significant results, independently of their p-values, are marked by (*****).

MRIcro (v1.9.1, https://people.cas.sc.edu/rorden/mricro/mricro.html; Rorden and Brett, 2000) was used to create the images presented in this chapter: thresholded maps of results corrected for multiple comparisons were overlaid on the *ch2* template (Holmes et al., 1998) provided by the software.

Clusters of significant size were further explored by analyzing the location of their local peaks, in order to appreciate their scope across the brain. Moreover, since these clusters may have a bigger impact on the research questions of this work, a more detailed report of the between-study heterogeneity and publication bias tests is provided in the text.

Heterogeneity will be discussed starting from the value of I^2, which will be interpreted according to the guidelines provided by Higgins and Thompson (2002). A value of I^2 over 50% suggests considerable heterogeneity, which warrants caution in the interpretation of the results. If I^2 is comprised between 30 and 50%, the between-study heterogeneity should be considered moderate, whereas if it is below 30% it is evaluated as mild.

Publication bias will be assessed with two methods. The first one is an Excess Significance test, whose interpretation is explained above. The second method is the analysis of funnel plots: these graphs show the distribution of standard errors of individual studies. If the plot is symmetric, publication bias may be excluded.

3.1.1 Cognitive Control

3.1.1.1 Encoding

The meta-analysis on Cognitive Control Encoding yielded six clusters of significant activation, whose details are reported in Table 3.1. A map of those same activations is available in Figure 3.1.

The main peaks of these clusters are located in the first section of the crus of the left cerebellum (Cluster 1), in the bilateral inferior parietal gyrus (IPG; Clusters 2 and 4), in the right supplementary motor area (SMA; Cluster 3), in the left posterior cingulate (Cluster 5), and in the triangular part of the right inferior frontal gyrus (IFG; Cluster 6).

Cl	Anatomical region	MNI			Voxels	Hedges' g			H^2	I^2	Excess Sign.(p)
		X	Y	Z		Est.	Var.	SDM-Z			
1	Left cerebellum, Crus I	-30	-70	-30	1,761	.414	.004	6.944	1.043	4.100	.993
2	Left inferior parietal gyrus	-46	-38	46	738	.355	.003	6.091	1.081	7.513	.628
3	Right supplementary motor area	6	20	54	585	.353	.003	6.395	1.058	5.513	.886
4	Right inferior parietal gyrus	54	-48	46	379	.401	.004	6.118	1.144	12.615	.973
5	Left posterior cingulate	0	-32	32	294	.321	.003	5.933	1.010	0.967	.611
6	Right inferior frontal gyrus, triangular part	50	24	2	151	.275	.003	4.990	1.011	1.100	$<.001$*

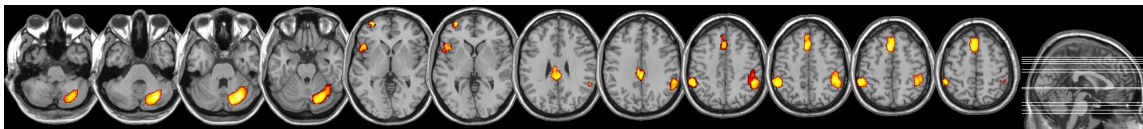Table 3.1: Statistics for the Cognitive Control Encoding meta-analysis.

Figure 3.1: Clusters of significant activation in Cognitive Control Encoding.

3.1.1.2 Violation

Five clusters of significant activation were found in the meta-analysis on Cognitive Control Violation. Their detailed statistics are reported in Table 3.2 and they can be visually appreciated in Figure 3.2.

The main peaks of these clusters are located in the left SMA (Cluster 1), in the triangular part of the left IFG (Cluster 2), in the right insula (Cluster 3), in the left IPG (Cluster 4), and in the opercular part of the right IFG (Cluster 5).

Cl	Anatomical region	MNI			Voxels	Hedges' g			H^2	I^2	Excess Sign.(p)
		X	Y	Z		Est.	Var.	SDM-Z			
1	Left supplementary motor area	-4	20	50	1,829	.479	.004	7.922	1.049	4.648	.730
2	Left inferior frontal gyrus, triangular part	-46	18	4	1,439	.372	.004	6.189	1.051	4.845	.997
3	Right insula	40	20	-4	597	.391	.012	3.548	3.406	70.639	.924
4	Left inferior parietal gyrus	-48	-36	44	287	.373	.004	5.693	1.142	12.432	.637
5	Right inferior frontal gyrus, opercular part	46	12	32	244	.305	.003	5.360	1.026	2.573	1.000

Table 3.2: Statistics for the Cognitive Control Violation meta-analysis.
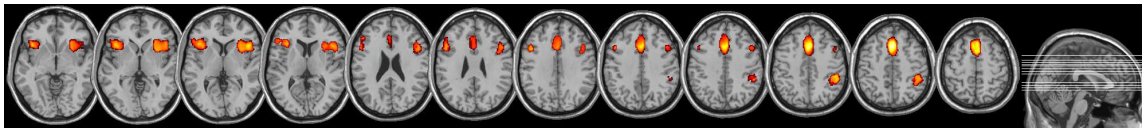
Figure 3.2: Clusters of significant activation in Cognitive Control Violation.

3.1.1.3 General

The meta-analysis on Cognitive Control General resulted in seven clusters of significant activation, whose details are reported in Table 3.3. A map of these clusters is shown in Figure 3.3.

The main peaks of these clusters are located in the left SMA (Cluster 1), in the bilateral insula (Clusters 2 and 3), in the left IPG (Cluster 4), in the right IFG (Cluster 5), in lobule IV of the left cerebellum (Cluster 6), and in the left posterior cingulate (Cluster 7).

Cl	Anatomical region	MNI			Voxels	Hedges' g			H^2	I^2	Excess Sign.(p)
		X	Y	Z		Est.	Var.	SDM-Z			
1	Left supplementary motor area	2	18	48	2,689	.459	.001	10.894	1.045	4.267	.854

Cl	Anatomical region	X	Y	Z	Voxels	Est.	Var.	SDM-Z	H²	I²	Excess Sign.(p)
2	Left insula	-28	16	-6	2,202	.341	.002	7.294	1.225	18.336	.854
3	Right insula	42	20	2	1,884	.351	.003	5.745	1.772	43.558	1.000
4	Left inferior parietal gyrus	-52	-42	42	1,682	.408	.002	9.166	1.064	6.014	.960
5	Right inferior frontal gyrus	48	-46	46	1,454	.344	.002	7.770	1.026	2.521	.955
6	Left cerebellum, Lobule IV	-30	-68	-26	646	.292	.002	6.407	1.060	5.678	.974
7	Left posterior cingulate	0	-34	32	209	.275	.002	6.471	1.007	0.649	.988

Table 3.3: Statistics for the Cognitive Control General meta-analysis.
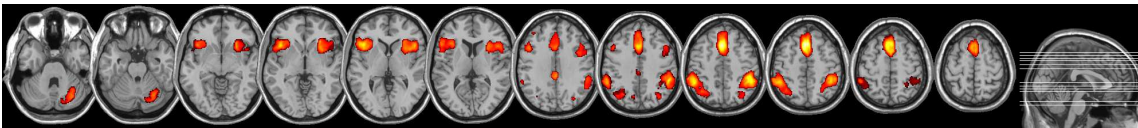
Figure 3.3: Clusters of significant activation in Cognitive Control General.

3.1.2 Attention

3.1.2.1 Encoding

The meta-analysis on Attention Encoding identified two clusters of significant activation (see Table 3.4 for a complete report). These clusters can be seen overlaid on a standard brain template in Figure 3.4.

The main peaks of these clusters are located in the right SMA (Cluster 1), and in the right inferior occipital gyrus (IOG, Cluster 2).

Cl	Anatomical region	MNI			Voxels	Hedges' g			H²	I²	Excess
		X	Y	Z		Est.	Var.	SDM-Z			Sign.(p)
1	Right supplementary motor area	2	4	52	27,082	.484	.006	6.494	1.028	2.701	.772

2	Right inferior occipital gyrus	40	-80	-10	582	.297	.010	3.042	1.365	26.756	.447

Table 3.4: Statistics for the Attention Encoding meta-analysis.

Figure 3.4: Clusters of significant activation in Attention Encoding.

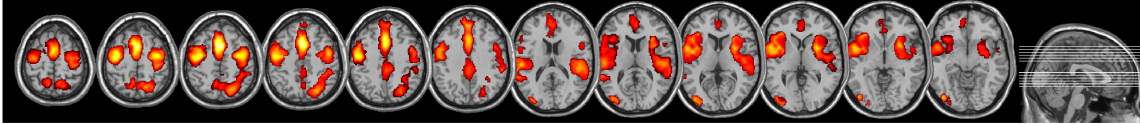Cluster 1 was further explored and was shown to extend in numerous brain areas. Its local peaks are located in the bilateral SMA, in the bilateral precentral gyrus (PrG), in the bilateral superior frontal gyrus (SFG; medial, medial-orbital and dorsolateral sections), in the bilateral putamen, in the bilateral IFG (triangular and opercular sections), in the bilateral insula, in the left superior parietal gyrus (SPG), in the bilateral superior temporal gyrus (STG), in the bilateral supramarginal gyrus (SMG), in the bilateral postcentral gyrus (PoG), in the bilateral anterior and median cingulate, in the bilateral precuneus (PCun), in the left IPG, in the right superior longitudinal fasciculus, in the left striatum, in the corpus callosum, in the right middle frontal gyrus (MFG), and in the left middle temporal gyrus (MTG). To summarize, Cluster 1 extends in wide areas in the bilateral frontal, parietal, and temporal lobes, with some subcortical involvement, especially of the insula.

Between-study heterogeneity is extremely low, meaning that differences in the methodology of the included experiments are not very influential on the results.

Although the Excess Significance test is not significant, the funnel plot is completely skewed to the right (see Figure 3.5), which does not allow for the exclusion of publication bias.
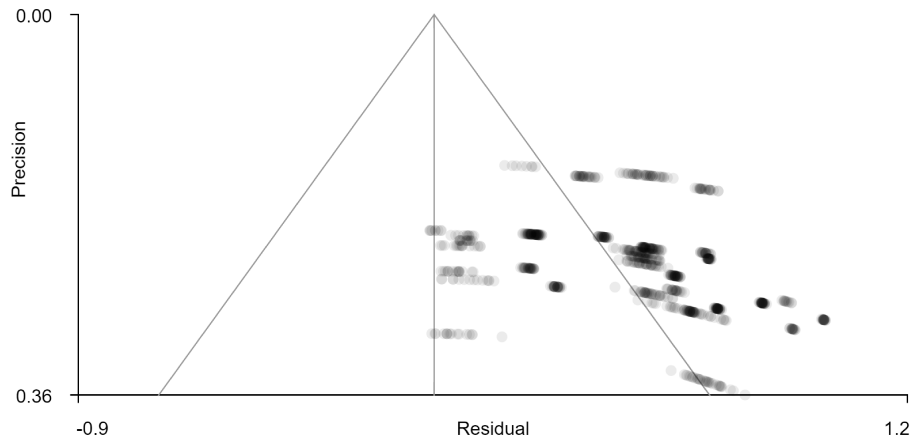

Figure 3.5: Funnel plot for Cluster 1 (right SMA) of the Attention Encoding meta-analysis.

3.1.2.2 Violation

The meta-analysis on Attention Violation indicated the presence of four clusters of significant activation. Their main statistics are reported in Table 3.5. Figure 3.6 allows the visual appreciation of these clusters.

The main peaks of these clusters are located in the right SMA (Cluster 1), in the opercular part of the left IFG (Cluster 2), in the left superior longitudinal fasciculus (Cluster 3), and in the left IPG (Cluster 4).

Cl	Anatomical region	MNI			Voxels	Hedges' g			H^2	I^2	Excess Sign.(p)
		X	Y	Z		Est.	Var.	SDM-Z			
1	Right supplementary motor area	4	8	56	12,848	.405	.002	8.644	1.312	23.776	.820
2	Left inferior frontal gyrus, opercular part	-48	8	26	1,868	.262	.002	5.384	1.382	27.644	1.000
3	Left superior longitudinal fasciculus III	-56	-38	12	878	.199	.002	4.342	1.230	18.717	.260
4	Left inferior parietal gyrus	-50	-46	44	582	.243	.002	5.487	1.067	6.244	.989

Table 3.5: Statistics for the Attention Violation meta-analysis.
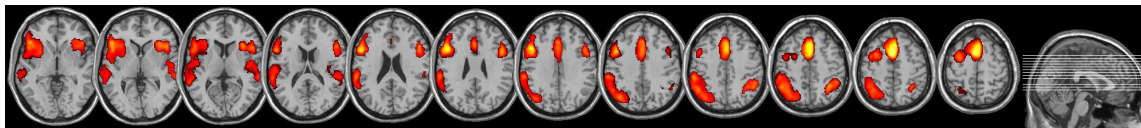
Figure 3.6: Clusters of significant activation in Attention Violation.

Cluster 1 was further explored: it contains local peaks in the bilateral SMA, in the right IFG (opercular, and triangular sections), in the right MFG, in the left SFG (medial section), in the left anterior and median cingulate, in the right SMG, in the right middle occipital gyrus (MOG), in the right IPG, in the right angular gyrus (AG), in the right STG, in the right SPG, in the right putamen, in the right PrG, in the right MTG, in the right insula, in the right superior occipital gyrus (SOG), and in the corpus callosum. In summary, Cluster 1 extends into a vast portion of the right hemisphere, spanning from the frontal to the occipital lobe, and less extensively into the left hemisphere, especially in the medial part of the frontal lobe. Some bilateral (but especially right) subcortical local peaks are also present.

Between-study heterogeneity is mild and raises no concerns about these specific results.

Although the Excess Significance test is not significant, publication bias cannot be fully excluded. As a matter of fact, the funnel plot for the right SMA (Figure 3.7) is very skewed to the right, making it impossible to rule out the presence of this kind of bias.
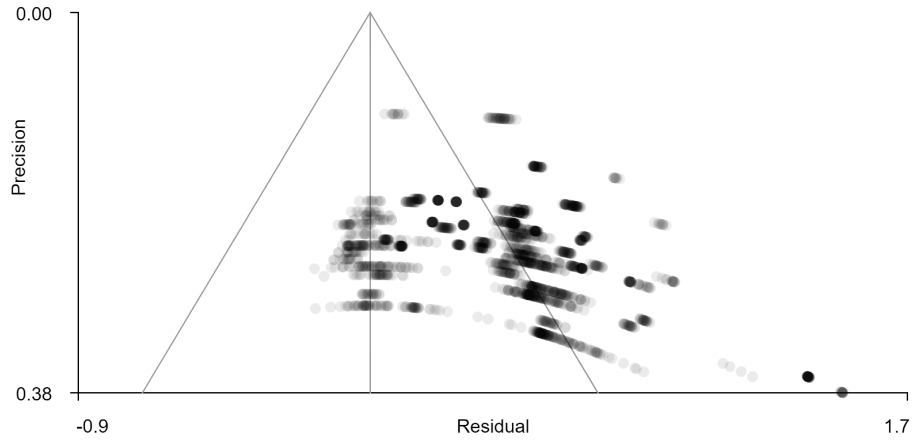
Figure 3.7: Funnel plot for Cluster 1 (right SMA) of the Attention Violation meta-analysis.

3.1.2.3 General

One cluster of significant activation was found in the meta-analysis on Attention General. Table 3.6 contains a precise description of its features. A map of this cluster is given in Figure 3.8.

Cl	Anatomical region	MNI			Voxels	Hedges' g			H^2	I^2	Excess Sign.(p)
		X	Y	Z		Est.	Var.	SDM-Z			
1	Right supplementary motor area	2	8	56	40,532	.436	.002	10.115	1.277	21.705	.972

Table 3.6: Statistics for the Attention General meta-analysis.
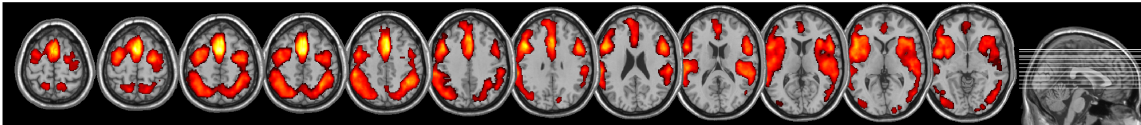
Figure 3.8: The cluster of significant activation in Attention General.

The main peak of Cluster 1 is located in the right SMA, but given its cluster size it was further explored. Local peaks were identified in the bilateral SMA, in the bilateral IFG (opercular, orbital, and triangular sections), in the bilateral SFG (medial, and medial-orbital sections), in the right MFG, in the bilateral PrG, in the bilateral IPG, in the bilateral SMG, in the left anterior cingulate, in the bilateral STG, in the bilateral insula, in the bilateral IOG, in the bilateral MOG, in the right

AG, in the bilateral MTG, in the corpus callosum, in the bilateral SPG, in the bilateral putamen, in the right SOG, in the left fusiform gyrus (FG), in the left striatum, in the bilateral PCun, in the bilateral inferior temporal gyrus (ITG), in the right PoG, and in hemispheric lobule VI and the crus of the left cerebellum. In summary, Cluster 1 spans nearly across the whole brain: it includes local peaks in all lobes of both hemispheres and in some subcortical structures (again, bilaterally).

Between-study heterogeneity is mild, as indicated by a value of I^2 lower than 30%.

Although the Excess Significance test is not significant, the funnel plot (Figure 3.9) is skewed to the right, raising some concerns about the presence of publication bias.
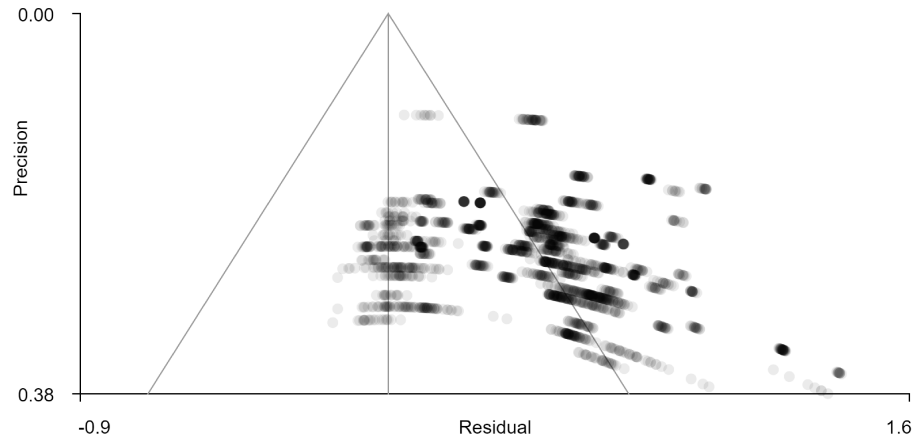
Figure 3.9: Funnel plot for Cluster 1 (right SMA) of the Attention General meta-analysis.

3.1.3   Language

3.1.3.1   Encoding

Four clusters of significant activation emerged in the meta-analysis on Language Encoding. The statistics for each one of them are available in Table 3.7. These clusters can also be visually appreciated in Figure 3.10.

The main peaks of these clusters are found in the triangular part of the left IFG (Cluster 1), in the right STG (Cluster 2), in the right median cingulate (Cluster 3), and in the second section of the crus of the right cerebellum (Cluster 4).

Cl	Anatomical region	MNI			Voxels	Hedges' g			H^2	I^2	Excess Sign.(p)
		X	Y	Z		Est.	Var.	SDM-Z			
1	Left inferior frontal gyrus, triangular part	-50	32	2	11,361	.377	.002	7.636	1.062	5.864	.966
2	Right superior temporal gyrus	58	-18	10	3,837	.340	.002	7.141	1.009	0.893	.434

| 3 | Right median cingulate | 2 | -36 | 38 | 1,293 | .299 | .002 | 6.516 | 1.016 | 1.621 | .995 |
| 4 | Right cerebellum, Crus II | 30 | -74 | -40 | 218 | .327 | .004 | 4.990 | 1.933 | 48.255 | .750 |

Table 3.7: Statistics for the Language Encoding meta-analysis.
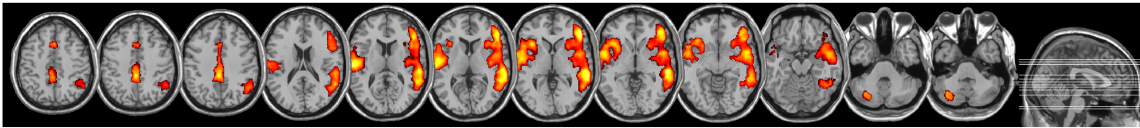
Figure 3.10: Clusters of significant activation in Language Encoding.

Local peaks for Cluster 1 are located in the left IFG (triangular, opercular, and orbital sections), in the left MTG, in the left STG, in the left AG, in the left ITG, in the left SMG, in the left insula, in the corpus callosum, in the left IPG, in the posterior segment of the left arcuate network, in the left striatum, and in the anterior commissure. In summary, Cluster 1 shows a strong left-lateralization, with local peaks in the left parietal, but especially frontal and temporal lobes. Some left subcortical and white matter structures are also involved.

Between-study heterogeneity is extremely low, excluding a role of the different methodologies used in the included experiments in determining these results.

Although the Excess Significance test is not significant, the funnel plot for this cluster (Figure 3.11) is skewed to the right, which does not allow to fully exclude publication bias.
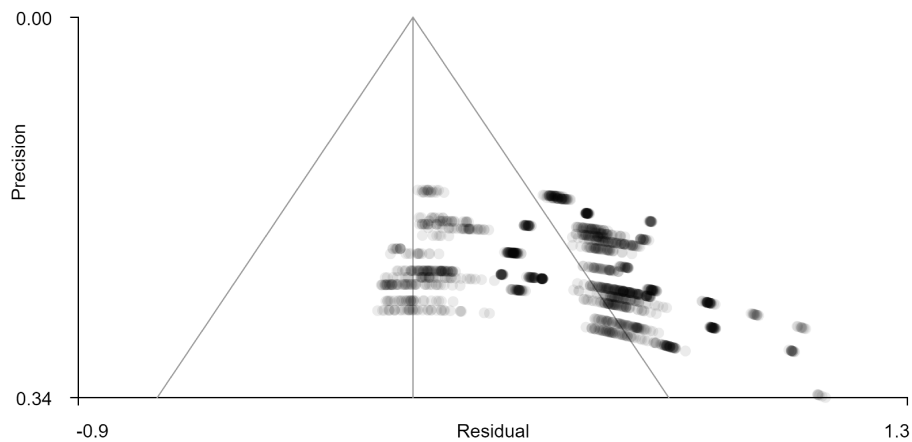
Figure 3.11: Funnel plot for Cluster 1 (triangular part of the left IFG) of the Language Encoding meta-analysis.

Cluster 2 shows local peaks in the right STG, in the right IFG (opercular section), in the

corpus callosum, in the right insula, and in the right putamen. This cluster therefore includes right-lateralized frontal and temporal areas, as well as some right subcortical structures.

Between-study heterogeneity is extremely low, meaning that the different methodologies used in the included studies do not influence the activation found in this cluster.

Once again, the Excess Significance test is not significant. Nonetheless, the presence of publication bias cannot be excluded since the funnel plot for this cluster (Figure 3.12) is skewed to the right.

Figure 3.12: Funnel plot for Cluster 2 (right STG) of the Language Encoding meta-analysis.

3.1.3.2 Violation

The meta-analysis on Language Violation resulted in three clusters of significant activation (see Table 3.8 for a more precise report). A map of these clusters is shown in Figure 3.13.

The main peaks of these clusters are located in the triangular part of the bilateral IFG (Clusters 1 and 2), and in the left medial SFG (Cluster 3).

Cl	Anatomical region	MNI			Voxels	Hedges' g			H^2	I^2	Excess Sign.(p)
		X	Y	Z		Est.	Var.	SDM-Z			
1	Left inferior frontal gyrus, triangular part	-48	28	20	6,650	.315	.002	7.106	1.046	4.393	1.000
2	Right inferior frontal gyrus, triangular part	52	30	10	4,463	.267	.006	3.482	2.470	59.519	1.000
3	Left medial superior frontal gyrus	-2	42	24	3,331	.288	.002	6.984	1.036	3.471	1.000

Table 3.8: Statistics for the Language Violation meta-analysis.
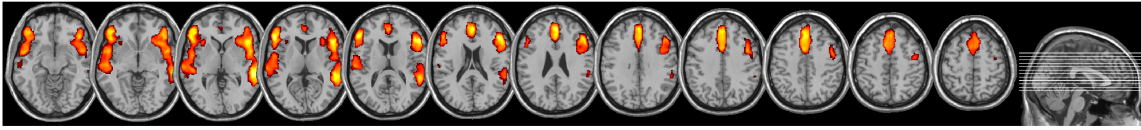
Figure 3.13: Clusters of significant activation in Language Violation.

The local peaks for Cluster 1 are found in the left IFG (triangular, opercular, and orbital sections), in the left MTG, in the left STG, in the left insula, in the left MFG, in the left PrG, and in the left SMG. In summary, Cluster 1 includes mainly areas from the left frontal and temporal lobes, reaching some subcortical and parietal structures as well.

Between-study heterogeneity is low, meaning that the differences in methodology do not particularly drive the results obtained.

Despite the Excess Significance test being not significant, publication bias cannot be excluded, as the funnel plot for this cluster (Figure 3.14) is skewed to the right.
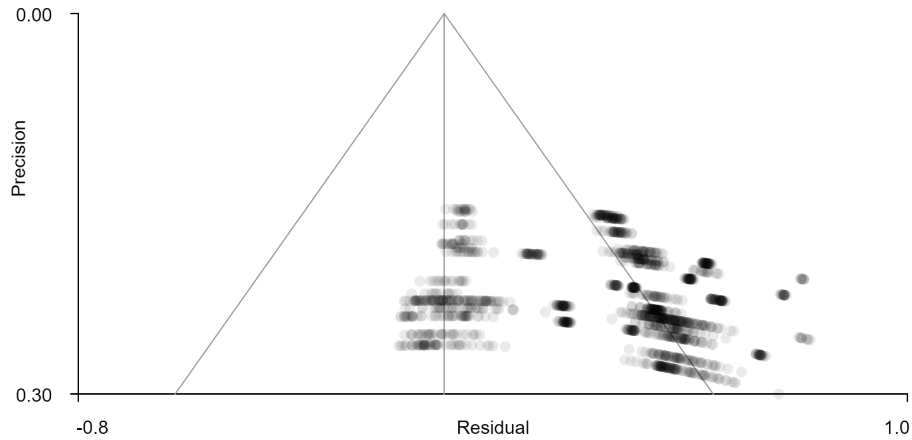

Figure 3.14: Funnel plot for Cluster 1 (triangular part of the left IFG) of the Language Violation meta-analysis.

Cluster 2 includes local peaks in the right IFG (triangular, opercular and orbital section), in the right superior longitudinal fasciculus, in the right STG, in the right insula, and in the right MTG. This cluster therefore is mainly right-lateralized and includes areas from the frontal and temporal lobes, and the insula.

Between-study heterogeneity is considerable, as the value of I^2 is over 50%. Therefore, it may be that the significant activation showed by this cluster is partly due to the high heterogeneity of the studies included.

The Excess Significance test for this cluster is not significant, and the funnel plot (Figure 3.15) is not as asymmetrical as the ones presented before. The presence of publication bias is therefore unlikely, although it is not possible to exclude it with certainty.
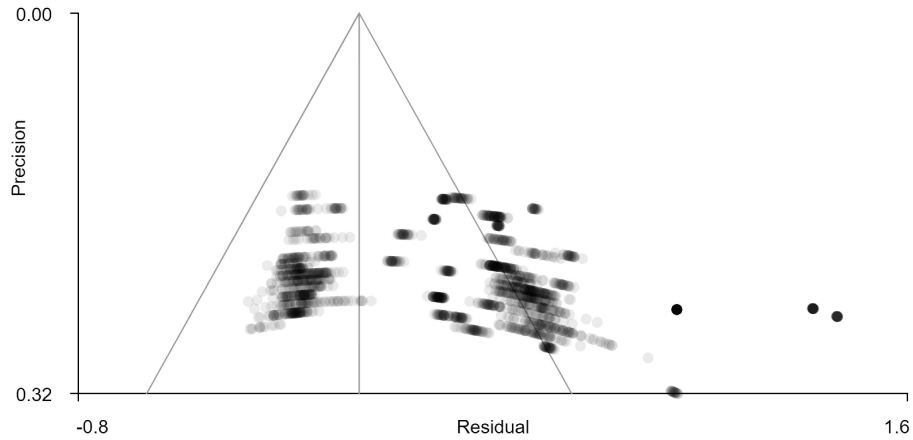
Figure 3.15: Funnel plot for Cluster 2 (triangular part of the right IFG) of the Language Violation meta-analysis.

3.1.3.3 General

The meta-analysis on Language General yielded three clusters of significant activation (see Table 3.9 for a more precise description). Figure 3.16 displays them on a standard brain template.

Their main peaks are located in the triangular part of the left IFG (Cluster 1), in the right Rolandic operculum (Cluster 2), and in the left median cingulate (Cluster 3). Given their size, all three clusters were further explored.

Cl	Anatomical region	MNI			Voxels	Hedges' g			H^2	I^2	Excess Sign.(p)
		X	Y	Z		Est.	Var.	SDM-Z			
1	Left inferior frontal gyrus, triangular part	-50	22	6	12,460	.319	.002	8.096	1.055	5.171	.561
2	Right Rolandic operculum	56	-18	12	8,110	.327	.002	7.420	1.484	32.622	<.001*
3	Left median cingulate	0	8	40	5,528	.281	.002	6.266	1.532	34.721	1.000

Table 3.9: Statistics for the Language General meta-analysis.
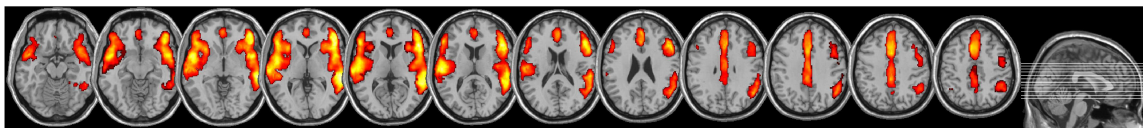
Figure 3.16: Clusters of significant activation in Language General.

Cluster 1 includes local peaks in the left IFG (triangular, opercular, and orbital sections), in the left MTG, in the left STG, in the left insula, in the left AG, in the left SMG, in the left ITG, in the left IPG, in the corpus callosum, in the left PrG, in the left PoG, in the left superior longitudinal fasciculus, in the posterior segment of the left arcuate network, in the left FG, and in the left MFG. In summary, Cluster 1 is left-lateralized and mainly includes areas of the frontal and temporal lobes, with some parietal and subcortical involvement.

Between-study heterogeneity is mild, as it is below the 30% threshold indicated by Higgins and Thompson (2002).

Although the Excess Significance test is not significant, it is not possible to fully exclude publication bias. As a matter of fact, the funnel plot for this cluster (Figure 3.17) is skewed to the right.
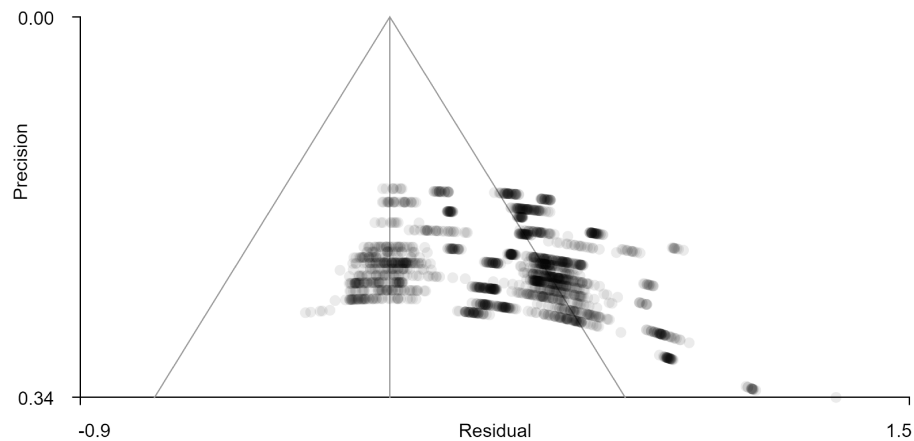

Figure 3.17: Funnel plot for Cluster 1 (triangular part of the left IFG) of the Language General meta-analysis.

Local peaks for Cluster 2 are located in the right Rolandic operculum, in the right STG, in the right IFG (triangular, opercular, and orbital sections), in the right insula, in the right superior longitudinal fasciculus, and in the right putamen. Cluster 2 therefore extends in the right frontal and temporal lobes, as well in some right subcortical structures.

Between-study heterogeneity is just above the 30% threshold, which can be considered moderate. The results found in this cluster should therefore be interpreted with some caution.

Publication bias has very likely influenced the significance of these results, as indicated by both the Excess Significance test and the funnel plot (Figure 3.18).
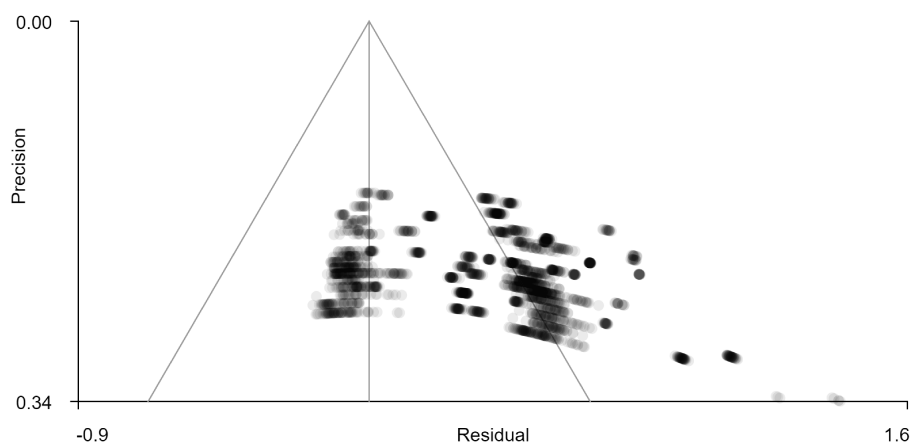
Figure 3.18: Funnel plot for Cluster 2 (right Rolandic operculum) of the Language General meta-analysis.

The local peaks of Cluster 3 are found in the bilateral median and anterior cingulate, in the left SFG (median section), in the bilateral SMA, and in the left PCun. In summary, this cluster encompasses cortical structures along the interhemispheric fissure bilaterally.

Between-study heterogeneity is just above the moderate threshold. Therefore, the results obtained in this cluster should be interpreted with some caution.

Despite the Excess Significance test being not significant, publication bias cannot be fully excluded. As a matter of fact, the funnel plot for this cluster (Figure 3.19) is skewed to the right.
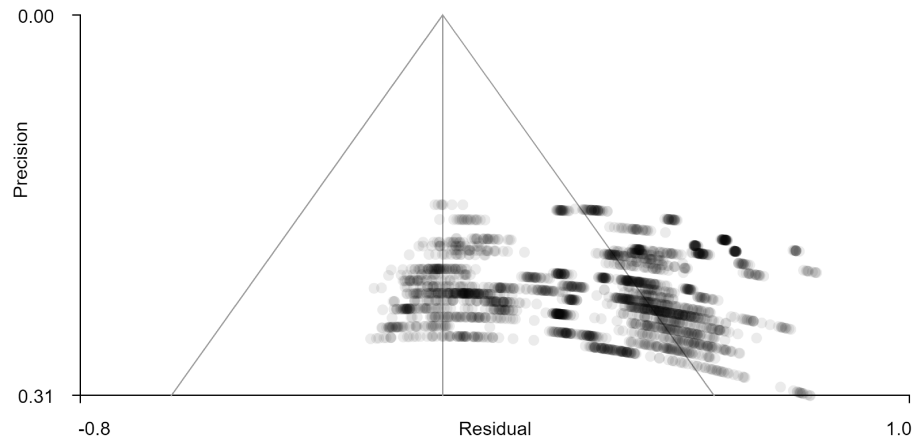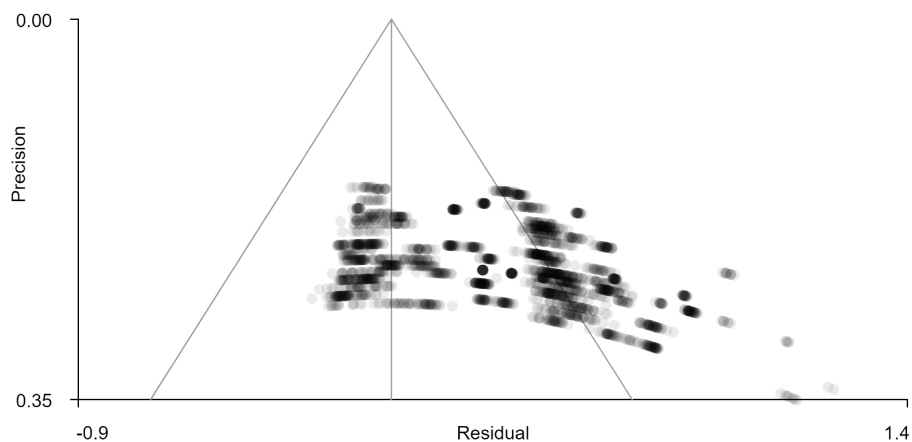

Figure 3.19: Funnel plot for Cluster 3 (left median cingulate) of the Language General meta-analysis.

3.1.4 Motor

3.1.4.1 Encoding

The meta-analysis on Motor Encoding highlighted six clusters of significant activation, whose detailed statistics are reported in Table 3.10. A map of these clusters can be found in Figure 3.20.

The main peaks for these clusters are located in the right median cingulate (Cluster 1), in the left IPG (Cluster 2), in the right SMG (Cluster 3), in the right striatum (Cluster 4), in an *undefined* brain region (Cluster 5), and in the right MFG (Cluster 6).

To better describe Cluster 5, whose main peak was located in an undefined area, its local peaks were explored. They are found in the bilateral anterior thalamic projections and in the corpus callosum, meaning that this cluster mainly extends into white matter.

Cl	Anatomical region	MNI			Voxels	Hedges' g			H^2	I^2	Excess Sign.(p)
		X	Y	Z		Est.	Var.	SDM-Z			
1	Right median cingulate	4	18	32	3,850	.355	.005	4.810	1.644	39.178	.995
2	Left inferior parietal gyrus	-50	-48	38	3,017	.439	.006	5.497	1.864	46.349	.726
3	Right supramarginal gyrus	58	-46	28	1,615	.315	.004	4.818	1.056	5.275	.933
4	Right striatum	26	-2	-8	1,097	.314	.004	5.249	1.005	0.482	.233
5	*Undefined*	-8	2	2	804	.381	.004	5.995	1.057	5.430	.643
6	Right middle frontal gyrus	34	34	34	148	.012	.004	0.197	1.006	0.631	.599

Table 3.10: Statistics for the Motor Encoding meta-analysis.
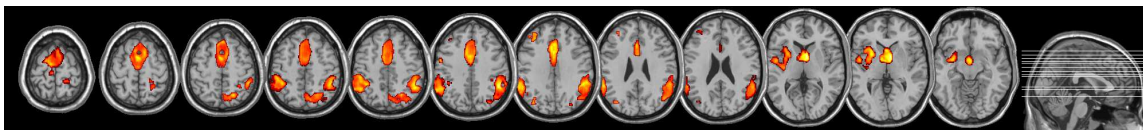
Figure 3.20: Clusters of significant activation in Motor Encoding.

3.1.4.2 Violation

The meta-analysis on Motor Violation yielded two clusters of significant activation. The statistics describing them can be found in Table 3.11. These clusters can be seen overlaid on a standard brain template in Figure 3.21.

Their main peaks are found in the right Rolandic operculum (Cluster 1), and in the right SMA (Cluster 2).

Cl	Anatomical region	MNI			Voxels	Hedges' g			H^2	I^2	Excess Sign.(p)
		X	Y	Z		Est.	Var.	SDM-Z			
1	Right Rolandic operculum	62	-10	10	3,643	.386	.006	5.185	1.222	18.168	.410
2	Right supplementary motor area	4	18	50	1,523	.422	.005	5.845	1.073	6.806	.655

Table 3.11: Statistics for the Motor Violation meta-analysis.
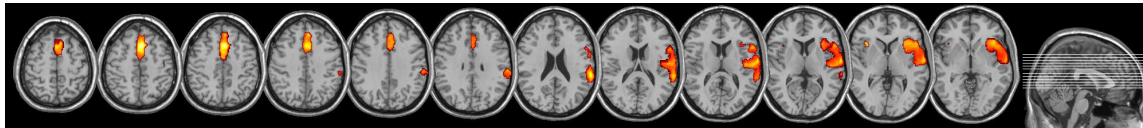
Figure 3.21: Clusters of significant activation in Motor Violation.

3.1.4.3 General

Five clusters of significant activation emerged from the meta-analysis on Motor General. See Table 3.12 for a report on their main statistics. A map of these clusters is provided in Figure 3.22.

The main peaks for these clusters are located in the lenticular nucleus of the right putamen (Cluster 1), in the left medial SFG (Cluster 2), in the left IPG (Cluster 3), in the left insula (Cluster 4), and in an *undefined* brain region (Cluster 5).

Cluster 5 was indicated by the software as encompassing an undefined region. Its local peaks fall into the bilateral anterior thalamic projections and in the left caudate nucleus, so this cluster is mainly subcortical.

Cl	Anatomical region	MNI			Voxels	Hedges' g			H^2	I^2	Excess Sign.(p)
		X	Y	Z		Est.	Var.	SDM-Z			
1	Right lenticular nucleus, putamen	28	18	0	12,117	.202	.008	2.279	2.738	63.473	.771

2	Left medial superior frontal gyrus	2	16	42	4,308	.395	.004	6.541	1.675	40.288	.994
3	Left inferior parietal gyrus	-50	-48	38	1,299	.304	.003	5.279	1.658	39.670	.951
4	Left insula	-34	10	0	793	.276	.003	4.797	1.274	21.507	.370
5	*Undefined*	-6	0	4	521	.392	.006	4.950	2.678	62.659	.702

Table 3.12: Statistics for the Motor General meta-analysis.
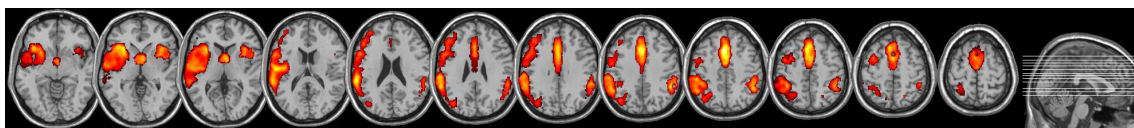
Figure 3.22: Clusters of significant activation in Motor General.

Cluster 1 includes local peaks in the right putamen, in the right Rolandic operculum, in the right STG, in the right insula, in the right SMG, in the right IPG, in the right IFG (opercular, and triangular sections), in the right PrG, in the right AG, in the right PoG, in the right MFG, in the right MOG, in the corpus callosum, in the right SPG, and in the anterior segment of the right arcuate network. Cluster 1 is therefore strongly right-lateralized, extending into areas mainly from the frontal and parietal lobes. Some subcortical structures are also included in this cluster.

Between-study heterogeneity is considerable, therefore results on this cluster should be interpreted with caution.

Publication bias can be excluded with a fair amount of certainty, as indicated by both the non-significant Excess Significance test and the nearly symmetric funnel plot (Figure 3.23).
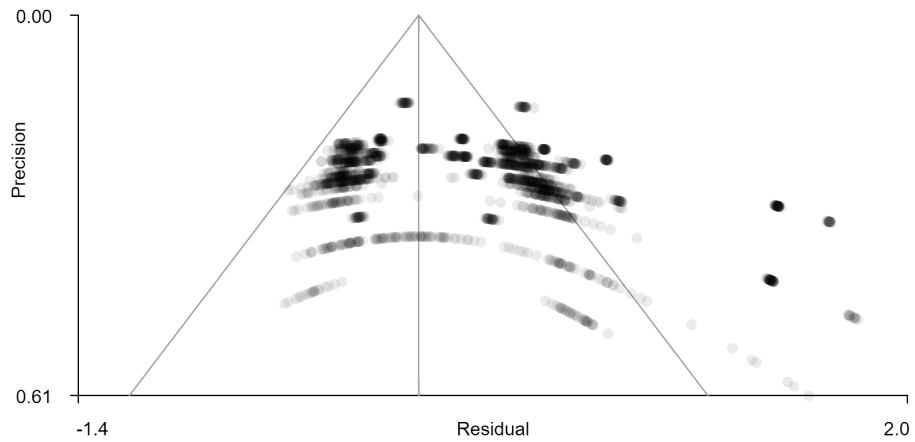
Figure 3.23: Funnel plot for Cluster 1 (lenticular nucleus of the right putamen) of the Motor General meta-analysis.

Local peaks for Cluster 2 are located in the bilateral SFG (medial section), in the bilateral anterior and median cingulate, and in the bilateral SMA. In summary, this cluster extends mainly in the medial part of the frontal lobe, bilaterally.

Between-study heterogeneity is mild in this cluster, which suggests some caution when interpreting these results.

Despite the Excess Significance test being not significant, the funnel plot (Figure 3.24) is not symmetric, with nearly all studies concentrated at the top of the funnel. Publication bias cannot therefore be excluded.
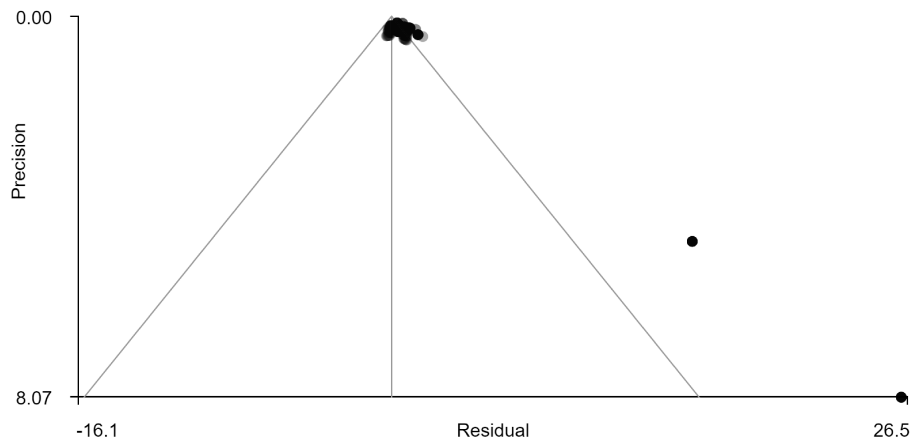
Figure 3.24: Funnel plot for Cluster 2 (left medial superior frontal gyrus) of the Motor General meta-analysis.

3.1.5 Social Cognition

3.1.5.1 Encoding

The meta-analysis on Social Cognition Encoding yielded no significant results.

3.1.5.2 Violation

The meta-analysis on Social Cognition Violation resulted in six clusters of significant activation, whose detailed statistics are reported in Table 3.13. Figure 3.25 shows the locations of these clusters.

The main peaks of these clusters are located in the bilateral medial SFG (Clusters 1 and 4), in the right Rolandic operculum (Cluster 2), in the right AG (Cluster 3), in the left PCun (Cluster 5), and in the right FG (Cluster 6).

Cl	Anatomical region	MNI			Voxels	Hedges' g			H^2	I^2	Excess Sign.(p)
		X	Y	Z		Est.	Var.	SDM-Z			
1	Left medial superior frontal gyrus	0	28	38	1,719	.291	.002	5.869	1.049	4.694	.943
2	Right Rolandic operculum	50	8	2	1,158	.265	.002	5.944	1.024	2.351	.876
3	Right angular gyrus	50	-64	26	827	.263	.002	5.524	1.097	8.858	.971
4	Right medial superior frontal gyrus	2	50	0	627	.268	.003	4.711	1.293	22.637	.362
5	Left precuneus	0	-48	40	372	.211	.002	4.632	1.002	0.185	.695
6	Right fusiform gyrus	38	-50	-24	277	.250	.002	5.307	1.005	0.518	.955

Table 3.13: Statistics for the Social Cognition Violation meta-analysis.
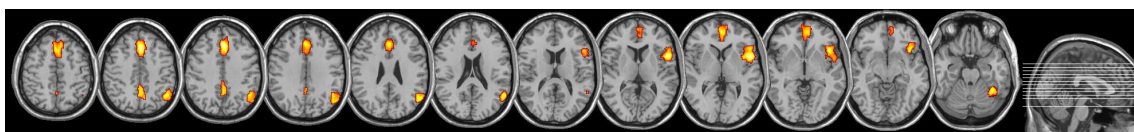
Figure 3.25: Clusters of significant activation in Social Cognition Violation.

3.1.5.3 General

Five clusters of significant activation were found in the meta-analysis on Social Cognition General. The statistics describing them can be found in Table 3.14. In Figure 3.26 their localization can be appreciated.

The main peaks of these clusters are found in the right insula (Cluster 1), in the right medial superior frontal gyrus (Cluster 2), in lobule VI of the right cerebellum (Cluster 3), in the left medial cingulate (Cluster 4), and in the left inferior parietal gyrus (Cluster 5).

Cl	Anatomical region	MNI			Voxels	Hedges' g			H^2	I^2	Excess Sign.(p)
		X	Y	Z		Est.	Var.	SDM-Z			
1	Right insula	38	20	-8	14,401	.306	.002	6.715	1.058	5.519	.784
2	Right medial superior frontal gyrus	2	48	0	2,483	.238	.002	5.199	1.071	6.660	.950
3	Right cerebellum, Lobule VI	36	-52	-24	857	.217	.002	4.713	1.020	2.007	.776
4	Left medial cingulate	0	-46	36	532	.165	.002	3.771	1.020	2.004	.382
5	Left inferior parietal gyrus	-54	-26	36	100	.189	.003	3.724	1.334	25.065	.688

Table 3.14: Statistics for the Social Cognition General meta-analysis.
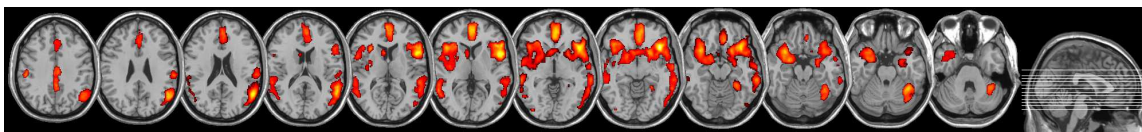
Figure 3.26: Clusters of significant activation in Social Cognition General.

Cluster 1 includes local peaks in the bilateral insula, in the bilateral IFG (opercular, orbital, and triangular sections), in the bilateral STG, in the bilateral striatum, in the uncinate fasciculus of the bilateral inferior network, in the left amygdala, in the right gyrus rectus, in the bilateral putamen, in the bilateral MTG, in the right AG, in the right ITG, in the right SMG, in the left caudate nucleus, in the posterior segment of the right arcuate network, in the cingulum of the right median network, in the right IOG, and in the right MOG. In summary, Cluster 1 extends bilaterally in the frontal and temporal lobes, as well as in the right parietal and occipital lobes. It also encompasses numerous subcortical structures bilaterally, together with some white matter connections.

Between-study heterogeneity is mild, meaning that it is unlikely that it has influenced the results.

Although the Excess Significance test is not significant, the funnel plot for this cluster (Figure 3.27) is skewed to the right, making it impossible to exclude the presence of publication bias.
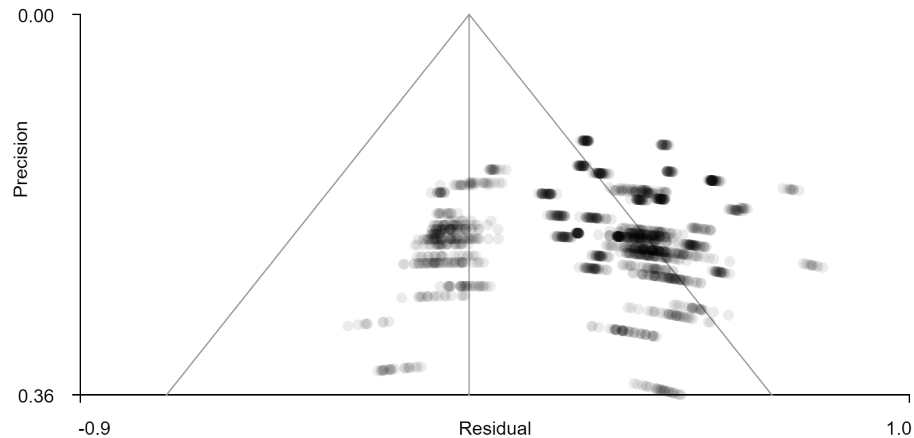
Figure 3.27: Funnel plot for Cluster 1 (right insula) of the Social Cognition General meta-analysis.

3.1.6 Overall

Unfortunately, the domain-general analyses for all conditions were not completed due to computational limitations. These analyses turned out to be extremely demanding in terms of computational power: three different computers were used in the attempt to obtain some results but none of them was powerful enough. This is in all likelihood due to the high number of experiments included in the meta-analyses (134 in Overall Encoding, 175 in Overall Violation, and 252 in Overall General).

3.2 Evaluation of risk of bias

Risk of bias was evaluated only on a subset of the papers from the Social Cognition meta-analyses by two independent raters using the AEROBICS (described in the *Materials and methods* chapter). The overall risk-of-bias ratings are reported in Table 3.15. The complete ratings, divided by rater, are available in Appendix D.

Reference	Rater 1	Rater 2
Bardi et al., 2016. Brain activation for spontaneous and explicit false belief tasks overlaps: new fMRI evidence on belief processing and violation of expectation.	Moderate	Some concerns
Boorman et al., 2013. The Behavioral and Neural Mechanisms Underlying the Tracking of Expertise.	Moderate	Some concerns

Cassidy and Gutchess, 2015. Neural Responses to Appearance-Behavior Congruity.	Moderate	Some concerns
Christopoulos and King-Casas, 2015. With you or against you: Social orientation dependent learning signals guide actions made for others.	Moderate	Moderate
Cloutier et al., 2011. An fMRI study of violations of social expectations: When people are not who we expect them to be.	Moderate	Moderate
Diaconescu et al., 2017. Hierarchical prediction errors in midbrain and septum during social learning - Study 1.	Moderate	Some concerns
Diaconescu et al., 2017. Hierarchical prediction errors in midbrain and septum during social learning - Study 2.	Moderate	Some concerns
Dungan et al., 2016. Theory of mind for processing unexpected events across contexts.	Moderate	Moderate
Dzafic et al., 2016. Dynamic emotion perception and prior expectancy.	Moderate	Moderate

Table 3.15: Overall risk-of-bias ratings for the evaluated papers from the Social Cognition meta-analyses.

3.2.1 Inter-rater reliability

The inter-rater reliability for the AEROBICS was calculated both on the overall risk-of-bias ratings and on the single domain-specific risk-of-bias ratings. Cohen's kappa for two raters was used as an index of inter-rater reliability. In Table 3.16 its value can be found, together with its significance.

Domain	Cohen's kappa	z	P
Participant selection	.40	1.50	.134
Experimental task	-.10	-0.95	.343
Support scales	.78	3.30	<.001
Statistics	-.11	-.067	.502
Overall	0		

Table 3.16: Inter-rater reliability of the AEROBICS domain-specific and overall risk-of-bias ratings

Already at first glance, it is clear that the inter-rater reliability of the AEROBICS is not great, nonetheless the results presented in Table 3.16 are here interpreted according to the guidelines provided by McHugh (2012).

Before analyzing these results more in detail, it is important to stress once again that this is the first time the AEROBICS is ever used to evaluate risk of bias. The results presented here should be therefore considered preliminary, similar to a checkpoint for the development of this tool.

The only significant result is the one for the domain *Support scales*: the value of Cohen's kappa indicates a moderate level of agreement, which is good considering that it is the first time the AEROBICS is used and tested.

Of the other results, the closest to significance is the one for the domain *Participant selection*. According to the guidelines provided by McHugh (2012), the raters agree in their evaluation weakly. Although there is definitely room for improvement, it is a starting point for further development.

Finally, the values of kappa for the domains *Experimental task* and *Statistics* are the lowest and least significant. According to McHugh (2012)'s guidelines, they would indicate the absence of agreement. The overall risk-of-bias rating has an inter-rater reliability of 0, which does not allow for any further discussion on it. Hypotheses for the reasons behind these low scores will be brought forward in the *Discussion* chapter.

3.2.2 Qualitative assessment of the AEROBICS by the raters

The raters were asked for their opinions on the AEROBICS, especially concerning the difficulty in its usage and its scoring system.

Rater 1 had significantly less experience in the research field and in the evaluation of risk of bias. They had the impression that, although the AEROBICS was easy to use, the ratings were driven by the information that was missing in papers rather than from their contents. At the end of the evaluation, when they had the possibility to review their ratings compared with the ones of Rater 2, they expressed some doubts on their own work: they believed that they were overzealous in the evaluation of the items, which led to more severe ratings of risk of bias.

Rater 2 was significantly more experienced and familiar with research and its customs, which led to greater flexibility in the use of the AEROBICS. They found the scale quite easy and quick to use and stated that the ratings it provided seemed reasonable considering their impressions on the papers.

The raters were also asked to provide suggestions for the improvement of the AEROBICS, based on their first-hand experience with it, which will constitute the foundations for future modifications to the tool presented later in the *Discussion* chapter.

Chapter 4

Discussion

4.1 Is there a predictive network in the brain?

In this work, the existence of a domain-general and various domain-specific predictive networks was investigated by conducting multiple meta-analyses using Seed-based d Mapping with Permutation of Subject Images (SDM-PSI, v6.22, https://www.sdmproject.com/; Albajes-Eizagirre et al., 2019a, 2019b).

The results of these analyses may contribute to a better understanding of how prediction is coded in the brain both within and across cognitive domains, thus helping to shed light on whether predictive coding truly is a unifying account of brain activity (Friston, 2010; Hohwy, 2016).

More specifically, there will be an attempt to provide tentative answers to the questions highlighted at the beginning of this work. As previously stated, they stress some of the points still baffling researchers when it comes to predictive coding being a general theory of brain functioning.

The images presented in this section, which allow the visualization of the clusters of significant activation in all meta-analyses at once, were created using MRIcroGL (v1.2.20220720, https://www.nitrc.org/projects/mricrogl) by overlaying thresholded maps of results corrected for multiple comparisons on the *mni152* template provided by the software.

4.1.1 Domain-specific prediction: different brain areas for different domains?

Generally, different brain areas are involved in prediction in different cognitive domains, as the results for the meta-analyses reported here show. From what appears from these analyses, prediction in a specific domain tends to involve the areas normally thought to be responsible for that specific function. This point will be further discussed concerning each domain considered, but in general it is in line with the basic principle of predictive coding: as pointed out at the beginning of this work, the mechanism first hypothesized by Rao and Ballard (1999) for visual perception (and then extended to the whole of cognition) described prediction as occurring at all levels of the visual hierarchy, therefore in the areas which normally elaborate visual stimuli.

In Cognitive Control, the areas showing significant activation across the included studies are all

part of a network thought to mediate cognitive control (Cole and Schneider, 2007). The results on the bilateral insula are of particular interest, as they support recent work indicating the anterior insulae as an under-appreciated hub for cognitive control (Molnar-Szakacs and Uddin, 2022).

Although having its main peak in the right Supplementary Motor Area (SMA), the cluster found for Attention is of notable size, nearly spanning across the whole brain. It is commonly known that different attentional networks exist in the brain and involve different areas across different lobes (for a review and further references, see Posner, 2012). The findings of the meta-analyses conducted here are therefore in line with the literature on the areas generally involved in attentional processes.

Language is classically considered to be left-lateralized in the brain, with linguistic processing taking place across multiple areas of the frontal and temporal lobes (Friederici and Gierhan, 2013). Once again, the knowledge found in the literature is in line with the results of the Language General meta-analysis, especially in what concerns Cluster 1. It is important to stress, however, that the right hemisphere plays a role as well in the processing and production of language (Lindell, 2006), which is reflected in Cluster 2. The interpretation of Cluster 3 is a bit more tricky: although some of its local peaks are located in the frontal lobe, which is classically linked to language, its subcortical components are more difficult to explain. Nonetheless, recent developments in the literature call for a more detailed analysis of the subcortical components of language processing (Murphy et al., 2022), which could help to shed light on the present results.

When it comes to the Motor domain, the role of the frontal and parietal lobe are well established in the literature, with the primary motor cortex being part of the frontal lobe and the parietal lobe providing sensorimotor integration (Rizzolatti and Luppino, 2001). The parietal lobe also carries out some purely motor functions (Fogassi and Luppino, 2005). The presence of some subcortical clusters is not surprising, as various subcortical structures are known to contribute to motor functions, although they carry out other functions as well (Di Martino et al., 2008). Once more, the results from the meta-analyses allow to support the idea that prediction for a specific domain happens in the same network that normally mediates that domain.

Finally, in Social Cognition the clusters showing significant activation are all located inside the so-called social brain (Frith and Frith, 2007), a vast group of brain regions responsible for the processing of signals relevant to social interaction.

4.1.2 Encoding *vs* Violation: are these processes mediated by specific brain areas?

Since the Overall meta-analyses were not completed due to their computational demands, the only way to answer this question is to qualitatively compare the results for Encoding and Violation in each of the cognitive domains considered. From there it would be possible to draw conclusions on some plausible differences in brain areas involved in the encoding and violation of predictions across domains.

It is important to remind the reader that previous meta-analytic work found significant convergence for prediction violation in the left inferior frontal gyrus (IFG) and in the left anterior insula (Ficco et al., 2021; for a more thorough discussion of the implications of such findings please see the *Introduction* chapter of this work).
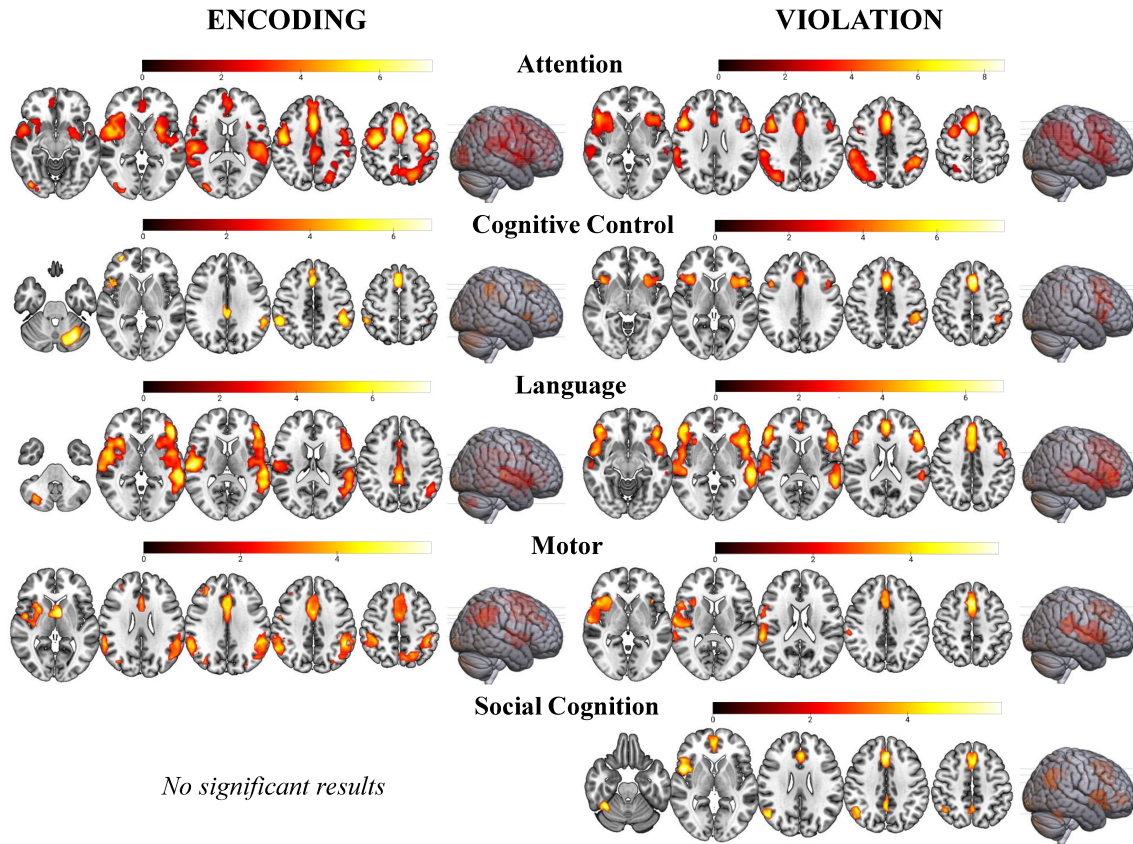
Figure 4.1: Main clusters of activation in all the domain-specific Encoding and Violation meta-analyses.

Given the results of the meta-analyses conducted here, it is possible to confirm to some extent the results reported by Ficco et al. (2021) and to expand their conclusions even further. All meta-analyses on Violation include in their clusters of significant activation either the IFG or the insula (in some cases both). Of note, the left lateralization for both areas found by Ficco et al. (2021) was not replicated in this work: depending on the considered domain, prediction violation resulted in significant activation in either hemisphere.

For example, in Cognitive Control both the Encoding and the Violation conditions include a cluster peaking in the right IFG, but in the latter condition there is also a cluster whose main peak is located in the right insula. In Attention, on the other hand, the left IFG is only involved in prediction violation, whereas the insula is a local peak of clusters from both conditions.

The activations in these areas are not so prominent as one could expect and it may seem rushed to draw these conclusions. Nonetheless, it is fundamental to stress a key factor: they are not drawn from data that are optimal for this purpose. As a matter of fact, the comparison of the domain-specific results does not allow to exclude the domain-specific activations discussed in the previous section. In other words, the activations specific for either prediction encoding or violation may be partly hidden by the domain-specific activations, which often include vast portions of the brain. This may be particularly true for the insula and IFG, which are involved in numerous functions

(some of which are included as domains in the meta-analyses; e.g., attention) due to their rich connectivity patterns (Liakakis et al., 2011; Uddin et al., 2017).

This limitation, however, allows for a further finding, which is made possible by the comparison of the Encoding and Violation conditions in each domain investigated. From this comparison, it emerges that the insula and the IFG, considered hubs of the prediction network identified by both Siman-Tov et al. (2019) and Ficco et al. (2021), are more involved in the processing of prediction violation rather than its encoding. Generalizing this conclusion, it could be argued that domain specificity in prediction is more linked to the encoding of predictions, whereas the processing of the violation of said predictions relies more on a general prediction network (discussed more in detail in the next paragraph).

4.1.3 A domain-general prediction network: insights from the domain-specific meta-analyses

Once again, the optimal way to further explore the existence of a prediction network in the brain would be to investigate it from the results of the Overall meta-analyses. As reported before, however, they were not completed due to their computational demands. Fortunately, it is possible to draw some conclusions from the qualitative comparison of the domain-specific meta-analyses.

Previous meta-analytic research (Ficco et al., 2021; Siman-Tov et al., 2019) reported the existence of a prediction network in the brain, spanning across multiple brain areas. In particular, these meta-analyses converge in suggesting a predominant role of the IFG and insula in prediction. Other areas deemed of importance for prediction include regions from the frontal, parietal, and temporal lobes, and some subcortical structures (e.g., caudate nucleus, cerebellum).

The results of the meta-analyses conducted here broadly supports the existence of the network first hypothesized by Siman-Tov et al. (2019) and then further explored by Ficco et al. (2021). In particular, their findings about the insula and the IFG (although not left-lateralized) are replicated, further confirming the importance of these brain regions in prediction. The unique approach taken by this work allowed to take this conclusion a little further: the results of the Violation meta-analyses highlighted that these regions may play a more prominent role in the processing of prediction violation.

No strong conclusions can be drawn on the other areas included by Siman-Tov et al. (2019) and Ficco et al. (2021) in the prediction network. Nearly all of them appear as either a main or a local peak in the clusters of significant activation, but not as predominantly as the IFG or the insula. Given that these conclusions are drawn from the domain-specific General meta-analyses, it is not possible to exclude that these areas are found significantly active due to their contribution to domain-specific processing.

Attention

Cognitive Control

Language

Motor

Social Cognition

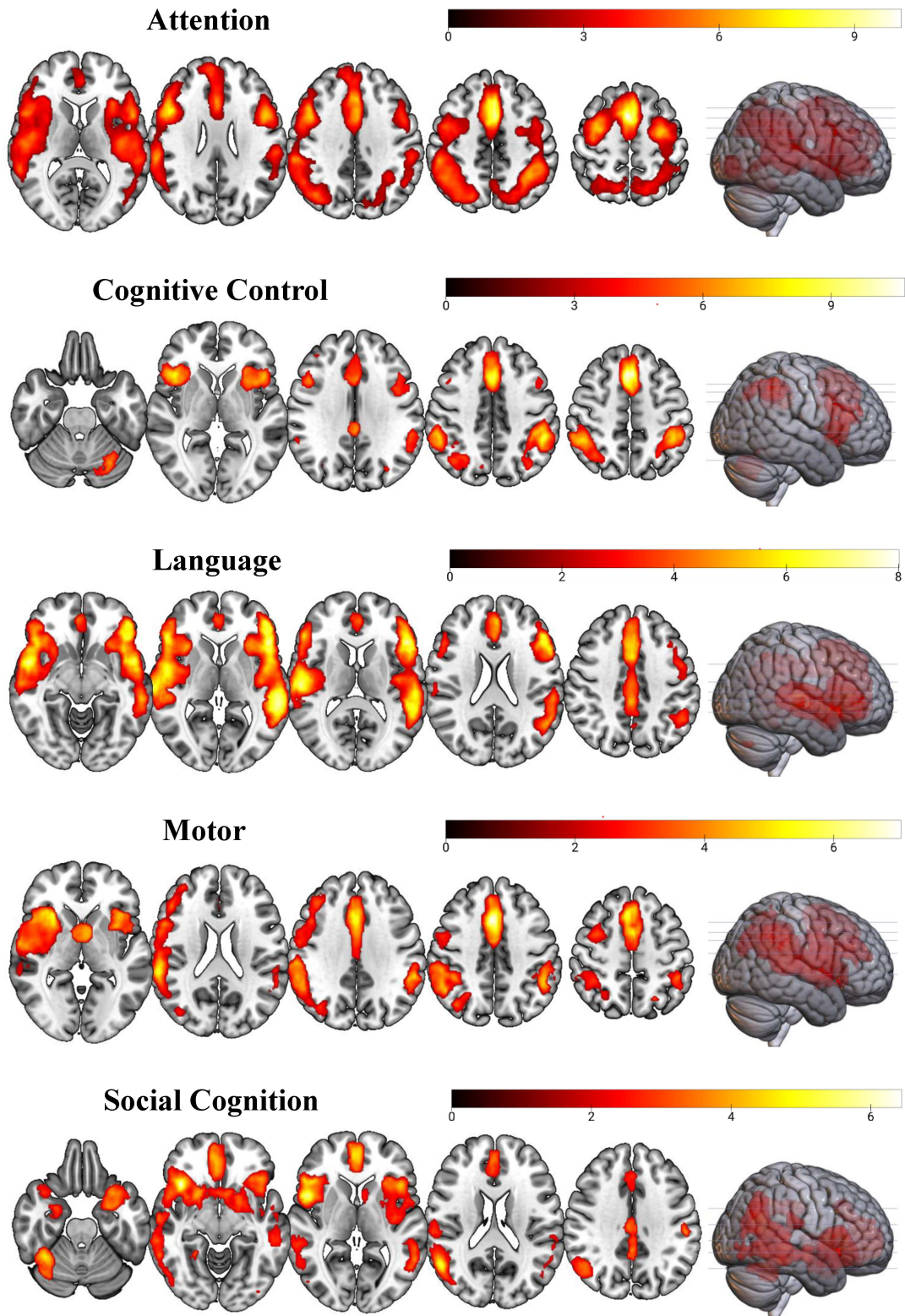Figure 4.2: Main clusters of activation in all the domain-specific General meta-analyses.

4.1.4 Limitations of the meta-analyses

First and foremost, the impossibility to complete the Overall meta-analyses deeply hindered the capacity to draw reliable conclusions from the results of this work. Because of this, it is vital to replicate these findings either with another software or with a computer equipped with sufficient computational power. Of note, an effort to conduct these analyses on the same datasets with Activation Likelihood Estimation (ALE; Eickhoff et al., 2009, 2012) has already been made and is being prepared for publication (Costa et al., 2023b).

This need for replication is more obvious for the last two research questions presented here. As a matter of fact, the conclusions drawn about the different areas involved in prediction encoding and violation, and the prediction network would greatly benefit from quantitative evidence backing them up. Although the qualitative comparison of the data from the domain-specific meta-analyses provides a good foundation to build some conclusions, the results of the domain-general analyses would allow to exclude domain-specific influences. It would be therefore possible to draw conclusions with a lesser amount of uncertainty.

4.2 The AEROBICS and the evaluation of risk of bias

This work represents the first instance in which the AEROBICS was used to evaluate risk of bias in the papers included in a meta-analyses, so the results presented here should be considered preliminary. This tool was developed from the PECANS Checklist (Costa et al., 2023a) to provide a quick and easy way to assess risk of bias in papers reporting cognitive studies before including them in a review and/or meta-analysis.

As previously stated, a lot of work still needs to be put in the development of the AEROBICS before it is ready to be published and widely used. As a prime example, its inter-rater reliability is bad to say the least, so much so that it is null on the *Overall* risk-of-bias rating. The agreement on the *Experimental task* and *Statistics* domains was non-existent as well, but the values of Cohen's kappa for the *Participant selection* and especially *Support scales* domains show the potential of the AEROBICS in the evaluation of risk of bias.

In order to highlight the future directions of the development of the AEROBICS, its main limitations will be here presented, as overcoming them will be the key process in the finalization of this scale.

4.2.1 Limitations of the AEROBICS

The first limitation of the AEROBICS is inherent to its nature: as the authors of the Cochrane instruments for the evaluation of risk of bias (Higgins et al., 2019; Sterne et al., 2016, 2019) point out, judging risk of bias will always retain a subjective component, which causes expertise to play a major role in the evaluation. That is to say, the more research experience the user of the AEROBICS has, the more reliable their ratings are supposed to be. This was evident in the data presented here as well: Rater 1 was significantly less experienced than Rater 2, which led the two raters to rate risk of bias very differently. This is also reflected in the inter-rater reliability scores

of the AEROBICS.

Going more into the specifics of the AEROBICS, the explanation of its scoring system at the beginning of the protocol may be misleading, especially for raters with less experience. Although the scoring system based on judgments and quartiles proved easy to use, the instructions on how to formulate a risk-of-bias rating led Rater 1 to make extremely harsh judgments, which in turn led to higher risk-of-bias ratings on single domains and overall.

Finally, the phrasing on some of the items was ambiguously interpreted by the two raters, resulting in differences in the risk-of-bias judgment for single domains and overall. It was possible to identify some items or groups of items phrased similarly whose ratings were most different between raters. For example, the difference between neuropsychological evaluation and questionnaire was not so clear to the raters, so much so that one paper was judged to contain a neuropsychological evaluation by one rater and a questionnaire by the other. Once again, expertise played a prominent role in the evaluation of these items: when an item's interpretation was ambiguous, Rater 1 chose to follow the interpretation leading to the harshest risk-of-bias rating, whereas Rater 2 relied on their expertise to provide a more balanced judgement.

4.2.2   Possible improvements and future work

As it emerged clearly, the AEROBICS as is is not a reliable measure of risk of bias. Nonetheless, it shows the potential to be a easy-to-use and quick way to provide a risk-of-bias judgement for papers before including them in a meta-analysis and/or review. The limitations described above can be solved with some changes to the current protocol of the AEROBICS.

First off, although it is impossible to completely remove subjectivity from the evaluation, it is possible to reduce the role played by expertise, so that experienced and inexperienced raters alike can give more balanced risk-of-bias ratings. This can be achieved by providing some commented examples of the evaluation of papers, so that people first approaching this kind of research can be guided in using the AEROBICS. Moreover, this could possibly ensure that the scale is used how its authors intended, thus overcoming one of the limitations of the Cochrane instruments for the evaluation of risk of bias pointed out by Igelström et al. (2021).

Second, the instructions at the beginning of the protocol can be modified, so that more details are given as to how risk of bias should be evaluated. This will be particularly useful for less experienced researchers. For example, raters are now instructed to evaluate risk of bias as *high* if no information is available on that specific item. In some cases, this led to wrong ratings by Rater 1: items 31 and 33 refer respectively to the presence of an outlier analysis and the handling of missing data, which are often not explicitly described in papers. Given that, Rater 1 often concluded for *high* risk of bias concerning these items, whereas Rater 2, being more familiar with research custom, was able to identify where these statistical procedure where referred to in the paper and therefore provide a more balanced rating. This ambiguity could easily be solved by being more specific in the instructions; for example by reporting the cases in which missing information is not problematic or how information concerning different items may be reported in papers.

Finally, to solve the ambiguity in the interpretation of items, it would be useful to provide some guidelines describing each item and what should be considered to provide a risk-of-bias judgment for

it. Some may argue that changing the phrasing would be easier, which is technically true, but there is a reason why keeping the current phrasing is the best alternative. As previously pointed out, the AEROBICS was developed starting from the PECANS checklist (Costa et al., 2023a), which in turn was developed by a Delphi panel of experts on the evaluation of the quality of cognitive studies. This means that items were phrased in a certain way as it was the most in line with the current theoretical knowledge. Therefore, providing guidelines would be a great compromise between adhering to scientific standards and guiding researchers in providing better evaluations of risk of bias. Supplementary guidelines are not unheard of, as this approach has already been used by the authors of the PRISMA guidelines (Moher et al., 2010; Page et al., 2021a). With each edition of the PRISMA statement, as a matter of fact, a supplementary paper is published in which each item of the PRISMA Checklist and its evaluation are described in detail (Liberati, 2009; Page et al., 2021b).

Chapter 5

Conclusion

5.1 Predictive processing

The analyses presented in this work allowed to provide an answer (although not definitive) to the questions highlighted at its beginning.

First, the results of the domain-specific General meta-analyses support the basic workings of predictive coding, as described by Rao and Ballard (1999) in their model of visual perception: according to the data presented here, domain-specific prediction is in part mediated by the same areas thought to normally process signals linked to that domain. Quite importantly, the results of the meta-analyses do not support the fact that these areas work alone in mediating prediction (as pointed out in the next paragraphs).

Secondly, through the qualitative comparison of the results of each couple of domain-specific Encoding and Violation meta-analyses, the more prominent role of the insula and the inferior frontal gyrus (IFG) in processing prediction violation, first hypothesized by Ficco et al. (2021), is replicated. Of note, the results obtained here do not support the left-lateralization found by Ficco et al. (2021).

Finally, some conclusions are drawn on the very existence of the prediction network by qualitatively comparing the results of the domain-specific General meta-analyses. Of the areas identified by Siman-Tov et al. (2019) and Ficco et al. (2021), only the role of the insula and the IFG is replicated. Due to the fact that this inference is not produced from optimal data, it is not possible to draw conclusions on any other area previously hypothesized as part of the prediction network due to the possible influence of domain-specific processing, which cannot be fully excluded.

5.2 Risk of bias

At the beginning of this work, the absence of an instrument to evaluate risk of bias in cognitive studies was highlighted. Such an instrument was therefore developed, starting from the Preferred Evaluation of Cognitive and Neuropsychological Studies (PECANS) Checklist (Costa et al., 2023a). It was named Analysis & Evaluation of Risk Of Bias in Cognitive Studies (AEROBICS) and used

by two raters to evaluate risk of bias in a subset of the papers included in the Social Cognition meta-analyses in this preliminary study. The AEROBICS proved easy and quick to use, thus showing potential for widespread use in research. Nonetheless, its inter-rater reliability is bad, which shows the need of more work to achieve the standards for publication. Some possible improvements have already been identified and will be put in place in the near future to further develop the AEROBICS.

Appendix A

Research strings for the meta-analyses on predictive processing

For each database searched, the general research string will be provided, together with a table containing the domain-specific string for each cognitive domain investigated. The table will also report the number of papers found for each domain.

A.1 PubMed

(((neuroimaging [Title/Abstract] OR fMRI[Title/Abstract] OR functional MRI [Title/Abstract]
OR magnetic resonance imaging[Title/Abstract] OR PET[Title/Abstract]) NOT
(DTI[Title/Abstract] OR Diffusion tensor Imaging[Title/Abstract] OR machine
learning[Title/Abstract] OR structural[Title/Abstract] OR tDCS[Title/Abstract] OR
TMS[Title/Abstract] OR EEG[Title/Abstract] OR intracranial[Title/Abstract]))
AND
(prediction[Title/Abstract] OR expectancy[Title/Abstract] OR expectation[Title/Abstract] OR
anticipation[Title/Abstract] OR unexpected[Title/Abstract] OR surpris*[Title/Abstract] OR
prediction error[Title/Abstract] OR incongruent[Title/Abstract] OR irregular[Title/Abstract] OR
violat*[Title/Abstract] OR mismatch[Title/Abstract] OR anticipat*[Title/Abstract])
AND
INSERT HERE THE DOMAIN-SPECIFIC SEARCH STRING
NOT (disease[Title/Abstract] OR disorder[Title/Abstract] OR pathology[Title/Abstract] OR
psychiat*[Title/Abstract] OR stroke[Title/Abstract] OR neurologic*[Title/Abstract] OR
Alzheimer[Title/Abstract] OR Parkinson[Title/Abstract] OR depression[Title/Abstract] OR
schizophrenia[Title/Abstract] OR dementia[Title/Abstract] OR neglect[Title/Abstract] OR
drug*[Title/Abstract] OR brain injury[Title/Abstract] OR surgery[Title/Abstract] OR

surgical[Title/Abstract] OR damag*[Title/Abstract] OR animal*[Title/Abstract] OR infants[Title/Abstract] OR adolescents[Title/Abstract] OR older[Title/Abstract] OR elderly[Title/Abstract] OR child*[Title/Abstract] OR phantom[Title/Abstract] OR rats[Title/Abstract] OR aphasi*[Title/Abstract] OR sign[Title/Abstract] OR adhd[Title/Abstract] OR deficit*[Title/Abstract] OR patient*[Title/Abstract] OR single-case[Title/Abstract] OR rodent*[Title/Abstract] OR review[Publication Type] OR meta-analysis[Publication Type] OR developmental[Title/Abstract] OR infants[Title/Abstract] OR surprisingly[Title/Abstract] OR unexpected results[Title/Abstract] OR unexpectedly[Title/Abstract] OR treatment[Title/Abstract] OR training[Title/Abstract] OR longitudinal[Title/Abstract])

Domain	Research string	Papers obtained
Cognitive Control	(executive function*[Title/Abstract] OR cognitive flexibility[Title/Abstract] OR perseverat*[Title/Abstract] OR cognitive control[Title/Abstract] OR error-monitoring[Title/Abstract] OR error monitoring[Title/Abstract] OR error detection[Title/Abstract] OR cognitive conflict[Title/Abstract])	200 results
Attention	(spatial attention[Title/Abstract] OR external attention[Title/Abstract] OR selective attention[Title/Abstract] OR sustained attention[Title/Abstract] OR focused attention[Title/Abstract] OR alternated attention[Title/Abstract] or divided attention[Title/Abstract] OR visual attention[Title/Abstract] OR attention[Title/Abstract])	373 results

Language	(language[Title/Abstract] OR linguistic[Title/Abstract] OR semantic*[Title/Abstract] OR syntactic[Title/Abstract] OR phonological[Title/Abstract] OR pragmatic*[Title/Abstract])	410 results
Motor	(motor[Title/Abstract] OR motor planning[Title/Abstract] OR movement[Title/Abstract] OR kinematic*[Title/Abstract])	436 results
Social Cognition	(social cognition[Title/Abstract] OR theory of mind[Title/Abstract] OR mentalizing[Title/Abstract] OR mindreading[Title/Abstract] OR mind-reading[Title/Abstract] OR mind reading[Title/Abstract] OR ToM[Title/Abstract] OR social learning[Title/Abstract])	73 results
Memory	(prospective memory[Title/Abstract] OR episodic memory[Title/Abstract] OR semantic memory[Title/Abstract] OR procedural memory[Title/Abstract] OR long-term memory[Title/Abstract] OR working memory[Title/Abstract] OR short-term memory[Title/Abstract])	192 results
Music	(music*[Title/Abstract] OR harmonic[Title/Abstract] OR melodic[Title/Abstract] OR rhythmic[Title/Abstract])	40 results

Pain	pain[Title/Abstract]	143 results

The search on PubMed yielded a total of 1,867 results.

A.2   Embase

(neuroimaging OR fMRI OR functional MRI OR magnetic resonance imaging OR PET) NOT
(DTI OR Diffusion tensor Imaging OR machine learning OR structural OR tDCS OR TMS OR
EEG OR intracranial)
AND
(prediction OR expectancy OR expectation OR anticipation OR unexpected OR surpris* OR
prediction error OR incongruent OR irregular OR violat* OR mismatch OR anticipat*)
AND
INSERT HERE THE DOMAIN-SPECIFIC SEARCH STRING
NOT (disease OR disorder OR pathology OR psychiat* OR stroke OR neurologic*OR Alzheimer
OR Parkinson OR depression OR schizophrenia OR dementia OR neglect OR drug* OR brain
injury OR surgery OR surgical OR damag* OR animal* OR infants OR adolescents OR older OR
elderly OR child* OR phantom OR rats OR aphasi*OR sign OR adhd OR deficit OR patient*
OR single-case OR rodent* OR review OR meta-analysis OR developmental OR infants OR
surprisingly OR unexpected results OR unexpectedly OR treatment OR training OR longitudinal)

The results were then filtered to limit them to papers in English describing studies on humans
available on Embase only.

Domain	Research string	Papers obtained
Cognitive Control	(executive function* OR cognitive flexibility OR perseverat* OR cognitive control OR error-monitoring OR error monitoring OR error detection OR cognitive conflict)	124 results
Attention	(attention)	267 results

Language	(language OR semantic* OR syntactic OR pragmatic*)	165 results
Motor	(motor planning OR movement OR kinematic*)	278 results
Social Cognition	(social cognition OR theory of mind OR mentalizing OR mindreading OR mind-reading OR mind reading OR ToM OR social learning)	115 results
Memory	(prospective memory OR episodic memory OR semantic memory OR procedural memory OR long-term memory OR working memory OR short-term memory)	69 results
Music	(music* OR harmonic OR melodic OR rhythmic)	49 results
Pain	(pain)	150 results

The search on Embase yielded a total of 1,217 results.

A.3 PsycInfo (ProQuest)

((ab(neuroimaging) OR ab(fMRI) OR ab(functional MRI) OR ab(magnetic resonance imaging) OR ab(PET)) NOT (ab(DTI) OR ab(Diffusion tensor Imaging) OR ab(machine learning) OR ab(structural) OR ab(tDCS) OR ab(TMS) OR ab(EEG) OR ab(intracranial)))
AND
INSERT HERE THE DOMAIN-SPECIFIC SEARCH STRING
AND
(ab(prediction) OR ab(expectancy) OR ab(expectation) OR ab(anticipation) OR ab(unexpected) OR ab(surpris*) OR ab(prediction error) OR ab(incongruent) OR ab(irregular) OR ab(violat*) OR ab(mismatch) OR ab(anticipat*))

NOT (ab(disease) OR ab(disorder) OR ab(pathology) OR ab(psychiat*) OR ab(stroke) OR ab(neurologic*) OR ab(Alzheimer) OR ab(Parkinson) OR ab(depression) OR ab(schizophrenia) OR ab(dementia) OR ab(neglect) OR ab(drug*) OR ab(brain injury) OR ab(surgery) OR ab(surgical) OR ab(damag*) OR ab(animal*) OR ab(infants) OR ab(adolescents) OR ab(older) OR ab(elderly) OR ab(child*) OR ab(phantom) OR ab(rats) OR ab(aphasi*) OR ab(sign) OR ab(adhd) OR ab(deficit) OR ab(patient*) OR ab(single-case) OR ab(rodent*) OR ab(review) OR ab(meta-analysis) OR ab(developmental) OR ab(infants)OR ab(surprisingly) OR ab(unexpected results) OR ab(unexpectedly) OR ab(treatment) OR ab(training) OR ab(longitudinal))

The results were then filtered to limit them to peer-reviewed papers in English describing studies on humans.

Domain	Research string	Papers obtained
Cognitive Control	(ab(executive function*) OR ab(cognitive flexibility) OR ab(@perseverat*) OR ab(cognitive control) OR ab(error monitoring) OR ab(error-monitoring) OR ab(error detection) OR ab(cognitive conflict))	271 results
Attention	(ab(attention))	338 results
Language	(ab(language) OR ab(semantic*) OR ab(syntactic) OR ab(pragmatic*))	316 results
Motor	(ab(motor) OR ab(motor planning) OR ab(movement) OR ab(kinematic*))	437 results
Social Cognition	(ab(social cognition) OR ab(theory of mind) OR ab(mentalizing) OR ab(mindreading) OR ab(mind-reading) OR ab(mind reading) OR ab(ToM) OR ab(social learning))	98 results

Memory	(ab(prospective memory) OR ab(episodic memory) OR ab(semantic memory) OR ab(procedural memory) OR ab(long-term memory) OR ab(working memory) OR ab(short-term memory)))	246 results
Music	(ab(music*) OR ab(harmonic) OR ab(melodic) OR ab(rhythmic))	54 results
Pain	(ab(pain))	29 results

The search on PsycInfo (ProQuest) yielded a total of 1,789 results.

Appendix B

Detailed report of study selection

B.1 Number of included experiments in each meta-analysis

Please note that the Overall meta-analyses also include experiments on Memory, Music and Pain. This explains why the sum of the experiments in the domain-specific meta-analyses is lower than the number of studies included in the domain-general meta-analyses.

General Prediction	
Overall General	252 experiments
Cognitive Control General	31 experiments
Attention General	52 experiments
Language General	52 experiments
Motor General	41 experiments
Social Cognition General	35 experiments

Prediction Encoding	
Overall Encoding	134 experiments
Cognitive Control Encoding	15 experiments
Attention Encoding	17 experiments
Language Encoding	32 experiments
Motor Encoding	28 experiments
Social Cognition Encoding	18 experiments

Prediction Violation	
Overall Violation	175 experiments
Cognitive Control Violation	21 experiments
Attention Violation	44 experiments
Language Violation	39 experiments
Motor Violation	18 experiments
Social Cognition Violation	29 experiments

B.2 PRISMA flow diagram (Page et al., 2021a)

PRISMA 2020 flow diagram for new systematic reviews which included searches of databases and registers only

Identification of studies via databases and registers

Identification

Records identified from*:
    PubMed (n = 1,867)
    Embase (n = 1,217)
    PsycInfo (ProQuest) (n = 1,789)

Records removed *before screening*:
    Duplicates automatically removed (n = 2,996)

Screening

Records screened
(n = 1877)

Records excluded**
(n = 1,285)
Duplicates manually removed (n = 183)

Reports sought for retrieval
(n = 409)

Reports not retrieved
(n = 0)

Reports assessed for eligibility
(n = 409)

Reports excluded:
    No whole brain analysis (n = 40)
    Use of techniques other than fMRI or PET (n = 6)
    No contrasts of interest (n = 36)
    Contained no coordinates (n = 11)
    Removed for other reasons (n = 64)

Included

Studies included in review
(n = 252)
Reports of included studies
(n = 252)

B.3 Complete list of papers included in the meta-analyses

Please note that the *Condition(s)* and *Domain(s)* columns specify in which process- and domain-specific meta-analyses data from the cited paper were included. Experiments on Memory, Music, and Pain were only included in the domain-general analyses.

For full references, the reader is directed to the Bibliography.

Reference	Domain(s)	Condition(s)
Aben et al., 2019. Context-dependent modulation of cognitive control involves different temporal profiles of fronto-parietal activity.	Attention	Violation
Alderson-Day et al., 2017. Distinct processing of ambiguous speech in people with non-clinical auditory verbal hallucinations.	Language	Encoding
Alho et al., 2015. Top-down controlled and bottom-up triggered orienting of auditory attention to pitch activate overlapping brain networks.	Attention	Violation
Alvarez et al., 2010. Functional anatomy of predictive vergence and saccade eye movements in humans: A functional MRI investigation.	Motor	Encoding
Andics et al., 2013. FMRI repetition suppression for voices is modulated by stimulus expectations.	Language	Encoding, Violation
Arrington et al., 2000. Neural Mechanisms of Visual Attention: Object-Based Selection of a Region in Space.	Attention	Violation
Atmaca et al., 2013. Prediction processes during multiple object tracking (MOT): involvement of dorsal and ventral premotor cortices.	Attention	Encoding
Aue et al., 2019. Expectancies influence attention to neutral but not necessarily to threatening stimuli: An fMRI study.	Attention	Violation
Bardi et al., 2016. Brain activation for spontaneous and explicit false belief tasks overlaps: new fMRI evidence on belief processing and violation of expectation.	Social Cognition	Encoding, Violation
Beldzik et al., 2015. Brain Activations Related to Saccadic Response Conflict are not Sensitive to Time on Task.	Cognitive Control	Violation
Bengtsson et al., 2009. Listening to rhythms activates motor and premotor cortices.	Music	Violation
Benn et al., 2014. The neural basis of monitoring goal progress.	Cognitive Control	Encoding
Bianco et al., 2016. Neural networks for harmonic structure in music perception and action.	Music	Violation
Blank and Von Kriegstein, 2013. Mechanisms of enhancing visual–speech recognition by prior auditory information.	Language	Violation

Blank et al., 2018. Neural Prediction Errors Distinguish Perception and Misperception of Speech.	Language	Violation
Blank and Davis, 2016. Prediction Errors but Not Sharpened Signals Simulate Multivoxel fMRI Patterns during Speech Perception.	Language	Encoding, Violation
Böckler et al., 2016. (How) observed eye-contact modulates gaze following. An fMRI study.	Attention	Encoding, Violation
Bohrn et al., 2012. Old Proverbs in New Skins – An fMRI Study on Defamiliarization.	Attention	Violation
Bonhage et al., 2015. Combined eye tracking and fMRI reveals neural basis of linguistic predictions during sentence comprehension.	Language	Encoding
Boorman et al., 2013. The Behavioral and Neural Mechanisms Underlying the Tracking of Expertise.	Social Cognition	Violation
Cacciaglia et al., 2019. Auditory predictions shape the neural responses to stimulus repetition and sensory change.	Attention	Violation
Cacioppo et al., 2014. Intention understanding over T: a neuroimaging study on shared representations and tennis return predictions.	Motor	Encoding, Violation
Cacioppo et al., 2017. Predicting Intentions of a Familiar Significant Other Beyond the Mirror Neuron System.	Social Cognition	Encoding
Campbell et al., 2021. Insula cortex gates the interplay of action observation and preparation for controlled imitation.	Motor	Encoding, Violation
Carp et al., 2010. Conditional differences in mean reaction time explain effects of response congruency, but not accuracy, on posterior medial frontal cortex activity.	Cognitive Control, Attention	Violation
Carter et al., 1995. Interference and Facilitation Effects during Selective Attention: An H215O PET Study of Stroop Task Performance.	Attention	Violation
Carvalho et al., 2016. Time-Perception Network and Default Mode Network Are Associated with Temporal Prediction in a Periodic Motion Task.	Attention	Violation
Cassidy and Gutchess, 2015. Neural Responses to Appearance-Behavior Congruity.	Social Cognition	Encoding, Violation
Cazzato et al., 2012. Mapping reflexive shifts of attention in eye-centered and hand-centered coordinate systems.	Motor	Violation
Chaminade et al., 2001. Is perceptual anticipation a motor simulation? A PET study.	Motor	Encoding
Chen and Desmond, 2005. Cerebrocerebellar networks during articulatory rehearsal and verbal working memory tasks.	Memory	Encoding, Violation

Chiu et al., 2017. The Caudate Nucleus Mediates Learning of Stimulus–Control State Associations.	Cognitive Control	Encoding
Chou et al., 2012. The role of inferior frontal gyrus in processing Chinese classifiers.	Language	Violation
Christensen et al., 2011. Neural Substrates of Attentive Listening Assessed with a Novel Auditory Stroop Task.	Attention	Violation
Christopoulos and King-Casas, 2015. With you or against you: Social orientation dependent learning signals guide actions made for others.	Social Cognition	Violation
Clos et al., 2014. Effects of prior information on decoding degraded speech: An fMRI study.	Language	Encoding, Violation
Cloutier et al., 2011. An fMRI study of violations of social expectations: When people are not who we expect them to be.	Social Cognition	Violation
Cohen et al., 2016. The Impact of Emotional States on Cognitive Control Circuitry and Function.	Cognitive Control	Encoding
Collins et al., 2017. Working Memory Load Strengthens Reward Prediction Errors.	Memory	Violation
Cooke et al., 2006. Large-scale neural network for sentence processing.	Language	Encoding
Cotti et al., 2011. Functionally dissociating temporal and motor components of response preparation in left intraparietal sulcus.	Motor	Encoding
Coull et al., 2016. Differential roles for parietal and frontal cortices in fixed versus evolving temporal expectations: Dissociating prior from posterior temporal probabilities with fMRI.	Attention	Encoding
Crafa et al., 2017. Heightened Responses of the Parahippocampal and Retrosplenial Cortices during Contextualized Recognition of Congruent Objects.	Memory	Encoding
Criaud et al., 2017. Testing the physiological plausibility of conflicting psychological models of response inhibition: A forward inference fMRI study.	Cognitive Control	Encoding
Cross et al., 2013. The influence of visual training on predicting complex action sequences.	Motor	Encoding
Danek et al., 2015. An fMRI investigation of expectation violation in magic tricks.	Motor	Violation
Danielsen et al., 2014. Investigating repetition and change in musical rhythm by functional MRI.	Music	Violation
Davis and Hasson, 2018. Predictability of what or where reduces brain activity, but a bottleneck occurs when both are predictable.	Attention	Violation
D'Cruz et al., 2011. Human reversal learning under conditions of certain versus uncertain outcomes.	Cognitive Control	Violation

Den Ouden et al., 2009. A Dual Role for Prediction Error in Associative Learning.	Attention	Violation
Den Ouden et al., 2010. Striatal Prediction Error Modulates Cortical Coupling.	Motor	Violation
Diaconescu et al., 2017. Hierarchical prediction errors in midbrain and septum during social learning.	Social Cognition	Encoding, Violation
Diekhof et al., 2011. The power of imagination — How anticipatory mental imagery alters perceptual processing of fearful facial expressions.	Social Cognition	Violation
Dietrich et al., 2019. Discourse management during speech perception: A functional magnetic resonance imaging (fMRI) study.	Language	Encoding
Domahs et al., 2013. Good, bad and ugly word stress – fMRI evidence for foot structure driven processing of prosodic violations.	Language	Encoding, Violation
Dombert et al., 2016. Functional mechanisms of probabilistic inference in feature- and space-based attentional systems.	Attention	Violation
Dungan et al., 2016. Theory of mind for processing unexpected events across contexts.	Social Cognition	Violation
Dunne and Opitz, 2020. Attention control processes that prioritise task execution may come at the expense of incidental memory encoding.	Memory	Encoding
Dzafic et al., 2016. Dynamic emotion perception and prior expectancy.	Social Cognition	Encoding, Violation
Eickhoff et al., 2011. Neural Correlates of Developing and Adapting Behavioral Biases in Speeded Choice Reactions–An fMRI Study on Predictive Motor Coding.	Motor	Encoding
Fajkus et al., 2015. An fMRI investigation into the effect of preceding stimuli during visual oddball tasks.	Attention	Violation
Fareri et al., 2012. Effects of Direct Social Experience on Trust Decisions and Neural Reward Circuitry.	Social Cognition	Violation
Farmer et al., 2019. The neural basis of shared preference learning.	Social Cognition	Violation
Fenker et al., 2010. "Virus and Epidemic": Causal Knowledge Activates Prediction Error Circuitry.	Language	Encoding
Flegal et al., 2014. Brain Mechanisms of Successful Recognition through Retrieval of Semantic Context.	Memory	Violation
Fletcher et al., 2001. Responses of human frontal cortex to surprising events are predicted by formal associative learning theory.	Cognitive Control	Violation
Foudil et al., 2020. Context-Dependent Coding of Temporal Distance Between Cinematic Events in the Human Precuneus.	Memory	Encoding

Friederici et al., 2009. Disentangling syntax and intelligibility in auditory language comprehension.	Language	Violation
Friedman et al., 2009. The brain's orienting response: An event-related functional magnetic resonance imaging investigation.	Attention	Violation
Frühholz et al., 2009. Interference control during recognition of facial affect enhances the processing of expression specific properties — An event-related fMRI study.	Social Cognition	Violation
Gagnepain et al., 2011. Is Neocortical–Hippocampal Connectivity a Better Predictor of Subsequent Recollection than Local Increases in Hippocampal Activity? New Insights on the Role of Priming.	Memory	Encoding
Gardner et al., 2015. Dynamic Modulation of the Action Observation Network by Movement Familiarity.	Motor	Encoding
Gayet et al., 2017. Visual Working Memory Enhances the Neural Response to Matching Visual Input.	Memory	Encoding, Violation
Gertz et al., 2016. Violating instructed human agency: An fMRI study on ocular tracking of biological and nonbiological motion stimuli.	Motor	Violation
Geuter et al., 2017. Functional dissociation of stimulus intensity encoding and predictive coding of pain in the insula.	Pain	Violation
Gordon et al., 2013. Social, reward, and attention brain networks are involved when online bids for joint attention are met with congruent versus incongruent responses.	Social Cognition	Encoding, Violation
Gottfried and Dolan, 2003. The Nose Smells What the Eye Sees: crossmodal visual facilitation of human olfactory perception.	Memory	Encoding
Grahn and Rowe, 2009. Feeling the Beat: Premotor and Striatal Interactions in Musicians and Nonmusicians during Beat Perception.	Music	Encoding, Violation
Grahn and Rowe, 2013. Finding and Feeling the Musical Beat: Striatal Dissociations between Detection and Prediction of Regularity.	Music	Encoding, Violation
Grewe et al., 2007. The role of the posterior superior temporal sulcus in the processing of unmarked transitivity.	Language	Encoding
Grotheer and Kovács, 2015. The relationship between stimulus repetitions and fulfilled expectations.	Social Cognition	Violation
Grotheer et al., 2014. Repetition probability effects for inverted faces.	Social Cognition	Encoding, Violation
Gruber et al., 2009. Brain mechanisms associated with background monitoring of the environment for potentially significant sensory events.	Attention	Violation

Gu et al., 2016. Neural Activities Underlying the Feedback Express Salience Prediction Errors for Appetitive and Aversive Stimuli.	Pain	Violation
Hagura et al., 2009. Visuokinesthetic Perception of Hand Movement is Mediated by Cerebro–Cerebellar Interaction between the Left Cerebellum and Right Parietal Cortex.	Motor	Encoding
Hakonen et al., 2017. Predictive processing increases intelligibility of acoustically distorted speech: Behavioral and neural correlates.	Language	Encoding
Ham et al., 2013. Cognitive Control and the Salience Network: An Investigation of Error Processing and Effective Connectivity.	Cognitive Control	Violation
Harlé et al., 2020. Proactive engagement of cognitive control modulates implicit approach-avoidance bias.	Cognitive Control	Violation
Harris and Fiske, 2010. Neural regions that underlie reinforcement learning are also active for social expectancy violations.	Social Cognition	Encoding, Violation
Haupt et al., 2009. Activation of the caudal anterior cingulate cortex due to task-related interference in an auditory Stroop paradigm.	Cognitive Control, Attention	Violation
Heil et al., 2019. Processing of Prediction Errors in Mentalizing Areas.	Social Cognition	Violation
Heim et al., 2009. The determiner congruency effect in language production investigated with functional MRI.	Language	Encoding, Violation
Heim et al., 2010. Left cytoarchitectonic BA 44 processes syntactic gender violations in determiner phrases.	Language	Encoding, Violation
Henco et al., 2020. Bayesian modelling captures inter-individual differences in social belief computations in the putamen and insula.	Social Cognition	Encoding, Violation
Henderson et al., 2020. Effect of Expectation on Pain Processing: A Psychophysics and Functional MRI Analysis.	Pain	Encoding
Henderson et al., 2016. Language structure in the brain: A fixation-related fMRI study of syntactic surprisal in reading.	Language	Encoding, Violation
Hillebrandt et al., 2013. Dynamic causal modelling of effective connectivity during perspective taking in a communicative task.	Social Cognition	Encoding
Hoenig and Scheef, 2005. Mediotemporal contributions to semantic processing: fMRI evidence from ambiguity processing during semantic context verification.	Language	Violation
Hoenig and Scheef, 2009. Neural correlates of semantic ambiguity processing during context verification.	Language	Violation

Holloway et al., 2015. Orthographic Dependency in the Neural Correlates of Reading: Evidence from Audiovisual Integration in English Readers.	Language	Violation
Hu et al., 2015. Anticipating conflict: Neural correlates of a Bayesian belief and its motor consequence.	Cognitive Control	Encoding
Hu et al., 2016a. Novelty Seeking, Harm Avoidance, and Cerebral Responses to Conflict Anticipation: An Exploratory Study.	Cognitive Control	Encoding
Hu et al., 2016b. The Right Superior Frontal Gyrus and Individual Variation in Proactive Control of Impulsive Response.	Cognitive Control	Encoding
Huang et al., 2012b. Brain Networks of Novelty-Driven Involuntary and Cued Voluntary Auditory Attention Shifting.	Attention	Encoding, Violation
Huang et al., 2012a. The role of left inferior frontal gyrus in explicit and implicit semantic processing.	Language	Violation
Hubers et al., 2016. How the brain processes violations of the grammatical norm: An fMRI study.	Language	Encoding
Ikeda et al., 2010. Cerebral activation associated with speech sound discrimination during the diotic listening task: An fMRI study.	Attention	Encoding, Violation
Jakobs et al., 2009. Effects of timing and movement uncertainty implicate the temporo-parietal junction in the prediction of forthcoming motor actions.	Motor	Violation
Johnson et al., 2016. Neural systems involved in processing novel linguistic constructions and their visual referents.	Language	Violation
Josse et al., 2012. The Brain's Dorsal Route for Speech Represents Word Meaning: Evidence from Gesture.	Language	Violation
Kandylaki et al., 2016. Predicting "When" in Discourse Engages the Human Dorsal Auditory Stream: An fMRI Study Using Naturalistic Stories.	Language	Encoding
Kawawaki et al., 2006. Anterior and superior lateral occipito-temporal cortex responsible for target motion prediction during overt and covert visual pursuit.	Motor	Encoding
Keidel et al., 2013. How Shakespeare tempests the brain: Neuroimaging insights.	Language	Violation
Kim et al., 2018. The benefits of negative yet informative feedback.	Cognitive Control	Encoding
Klasen et al., 2011. Supramodal Representation of Emotions.	Social Cognition	Encoding
Kluger and Schubotz, 2017. Strategic adaptation to non-reward prediction error qualities and irreducible uncertainty in fMRI.	Memory	Violation

Koelsch et al., 2005. Adults and children processing music: An fMRI study.	Music	Violation
Koelsch et al., 2002. Bach Speaks: A Cortical "Language-Network" Serves the Processing of Music.	Music	Violation
Koenen et al., 2018. From Anticipation to the Experience of Pain: The Importance of Visceral Versus Somatic Pain Modality in Neural and Behavioral Responses to Pain-Predictive Cues.	Pain	Encoding
Köhler et al., 2016. Differential involvement of brainstem noradrenergic and midbrain dopaminergic nuclei in cognitive control: NA and Dopaminergic Nuclei and Cognitive Control.	Cognitive Control	Violation
Kokonyei et al., 2019. Anticipation and violated expectation of pain are influenced by trait rumination: An fMRI study.	Pain	Encoding, Violation
Krasovsky et al., 2014. Differentiating Intended Sensory Outcome from Underlying Motor Actions in the Human Brain.	Motor	Encoding
Krebs et al., 2011. The Neural Underpinnings of How Reward Associations Can Both Guide and Misguide Attention.	Attention	Encoding
Krebs et al., 2015. Neural Conflict-Control Mechanisms Improve Memory for Target Stimuli.	Attention	Violation
Kristensen et al., 2013. The Interface Between Language and Attention: Prosodic Focus Marking Recruits a General Attention Network in Spoken Language Comprehension.	Attention, Language	Encoding, Violation
Krug and Carter, 2012. Proactive and reactive control during emotional interference and its relationship to trait anxiety.	Cognitive Control	Violation
Kudo et al., 2004. Selective activation and deactivation of the human brain structures between speeded and precisely timed tapping responses to identical visual stimulus: an fMRI study.	Motor	Encoding
Langner et al., 2011. Modality-Specific Perceptual Expectations Selectively Modulate Baseline Activity in Auditory, Somatosensory, and Visual Cortices.	Attention	Encoding
Laurienti et al., 2003. Cross-modal sensory processing in the anterior cingulate and medial prefrontal cortices.	Language	Encoding, Violation
Leaver et al., 2009. Brain Activation during Anticipation of Sound Sequences.	Music	Encoding
Lee et al., 2014. The neural bases of argument structure processing revealed by primed lexical decision.	Language	Violation
Lee and Noppeney, 2014. Temporal prediction errors in visual and auditory cortices.	Language	Encoding, Violation
Leong et al., 2017. Dynamic Interaction between Reinforcement Learning and Attention in Multidimensional Environments.	Attention	Violation

Leube et al., 2003. Observing one's hand become anarchic: An fMRI study of action identification.	Motor	Encoding
Li et al., 2014. Cognitive empathy modulates the processing of pragmatic constraints during sentence comprehension.	Language	Violation
Lim et al., 2020. Threat Prediction from Schemas as a Source of Bias in Pain Perception.	Pain	Encoding, Violation
Limanowski and Blankenburg, 2015. Network activity underlying the illusory self-attribution of a dummy arm: Network Activity of Illusory Self-Attribution.	Motor	Encoding
Limanowski et al., 2017. Neuronal correlates of continuous manual tracking under varying visual movement feedback in a virtual reality environment.	Motor	Violation
Lüttke et al., 2016. Preference for Audiovisual Speech Congruency in Superior Temporal Cortex.	Language	Encoding
Lyu et al., 2016. Predictive Brain Mechanisms in Sound-to-Meaning Mapping during Speech Processing.	Language	Encoding, Violation
Maffei et al., 2015a. Unfamiliar Walking Movements Are Detected Early in the Visual Stream: An fMRI Study.	Motor	Violation
Maffei et al., 2015b. Visual gravity cues in the interpretation of biological movements: neural correlates in humans.	Motor	Encoding
Malekshahi et al., 2016. Differential neural mechanisms for early and late prediction error detection.	Attention	Violation
Mancini et al., 2017. Disentangling meaning in the brain: Left temporal involvement in agreement processing.	Language	Encoding
Marini et al., 2016. Orchestrating Proactive and Reactive Mechanisms for Filtering Distracting Information: Brain-Behavior Relationships Revealed by a Mixed-Design fMRI Study.	Attention	Violation
Mastroberardino et al., 2015. Crossmodal semantic congruence can affect visuo-spatial processing and activity of the fronto-parietal attention networks.	Attention	Violation
Mayer et al., 2009. Neuronal modulation of auditory attention by informative and uninformative spatial cues.	Attention	Encoding, Violation
Mayrhauser et al., 2014. Neural repetition suppression: evidence for perceptual expectation in object-selective regions.	Attention	Violation
McAndrews et al., 2016. Semantic congruence affects hippocampal response to repetition of visual associations.	Memory	Encoding, Violation
Mead et al., 2002. Neural basis of the Stroop interference task: Response competition or selective attention?	Cognitive Control	Encoding, Violation

Mende-Siedlecki and Todorov, 2016. Neural dissociations between meaningful and mere inconsistency in impression updating.	Social Cognition	Encoding, Violation
Mestres-Missé et al., 2014. Dorsomedial striatum involvement in regulating conflict between current and presumed outcomes.	Language	Encoding, Violation
Mestres-Missé et al., 2017. Uncertainty and expectancy deviations require cortico-subcortical cooperation.	Cognitive Control	Encoding
Michelon et al., 2003. Neural correlates of incongruous visual information: An event-related fMRI study.	Attention	Violation
Milham et al., 2003. Competition for priority in processing increases prefrontal cortex's involvement in top-down control: an event-related fMRI study of the Stroop task.	Cognitive Control	Violation
Mill et al., 2015. Differentiating the Functional Contributions of Resting Connectivity Networks to Memory Decision-making: fMRI Support for Multistage Control Processes.	Memory	Violation
Moberget et al., 2014. Generalized Role for the Cerebellum in Encoding Internal Models: Evidence from Semantic Processing.	Language	Encoding, Violation
Morís Fernández et al., 2017. Audiovisual integration as conflict resolution: The conflict of the McGurk illusion.	Language	Encoding, Violation
Morís Fernández et al., 2015. Top-down attention regulates the neural expression of audiovisual integration.	Attention	Encoding, Violation
Nieuwland et al., 2012. Brain regions that process case: Evidence from Basque.	Language	Violation
Noppeney et al., 2008. The Effect of Prior Visual Information on Recognition of Speech and Sounds.	Language	Violation
Nuñez et al., 2005. Intentional false responding shares neural substrates with response conflict and cognitive control.	Cognitive Control	Violation
Ogawa et al., 2007. Neural Correlates of State Estimation in Visually Guided Movements: an Event-Related fMRI Study.	Motor	Encoding
Okada et al., 2018. Neural evidence for predictive coding in auditory cortex during speech production.	Language	Encoding
Ondobaka et al., 2015. Interplay Between Conceptual Expectations and Movement Predictions Underlies Action Understanding.	Motor	Encoding
O'Reilly et al., 2013. Dissociable effects of surprise and model update in parietal and anterior cingulate cortex.	Attention	Encoding, Violation
Osnes et al., 2012. Stimulus expectancy modulates inferior frontal gyrus and premotor cortex activity in auditory perception.	Music	Encoding

Park et al., 2019. Winning smiles: Signalling reward by overlapping and non-overlapping emotional valence differentially affects performance and neural activity.	Cognitive Control	Encoding
Pazen et al., 2020. Predictive perception of self-generated movements: Commonalities and differences in the neural processing of tool and hand actions.	Motor	Encoding
Peeters et al., 2017. Linking language to the visual world: Neural correlates of comprehending verbal reference to objects through pointing and visual cues.	Attention	Encoding, Violation
Pichon et al., 2016. Influence of Temporal Expectations on Response Priming by Subliminal Faces.	Attention	Violation
Potgieser and De Jong, 2016. Visuomotor Dissociation in Cerebral Scaling of Size.	Motor	Violation
Quiñones et al., 2014. Where agreement merges with disagreement: fMRI evidence of subject–verb integration.	Language	Violation
Raettig et al., 2010. Neural correlates of morphosyntactic and verb-argument structure processing: An EfMRI study.	Language	Encoding, Violation
Rahnev et al., 2011. Prior Expectation Modulates the Interaction between Sensory and Prefrontal Regions in the Human Brain.	Motor	Encoding
Ramnani and Miall, 2003. Instructed Delay Activity in the Human Prefrontal Cortex is Modulated by Monetary Reward Expectation.	Motor	Encoding
Ran et al., 2016. Prediction and unconscious attention operate synergistically to facilitate stimulus processing: An fMRI study.	Attention	Violation
Reichert et al., 2017. Functional brain networks during picture encoding and recognition in different odor contexts.	Memory	Violation
Reicherts et al., 2017. Anxious anticipation and pain: the influence of instructed *vs* conditioned threat on pain.	Pain	Encoding
Richter and De Lange, 2019. Statistical learning attenuates visual activity only for attended stimuli.	Attention	Violation
Rilling et al., 2004. Opposing BOLD responses to reciprocated and unreciprocated altruism in putative reward pathways.	Social Cognition	Encoding
Roberts and Hall, 2008. Examining a Supramodal Network for Conflict Processing: A Systematic Review and Novel Functional Magnetic Resonance Imaging Data for Related Visual and Auditory Stroop Tasks.	Cognitive Control	Encoding, Violation
Robertson et al., 2015. Dorsal striatum mediates cognitive control, not cognitive effort per se, in decision-making: An event-related fMRI study.	Cognitive Control	Encoding, Violation

Roelofs et al., 2006. Anterior cingulate cortex activity can be independent of response conflict in Stroop-like tasks.	Cognitive Control	Violation
Rothermich and Kotz, 2013. Predictions in speech comprehension: fMRI evidence on the meter–semantic interface.	Language	Violation
Russo et al., 2020. Semantics-weighted lexical surprisal modeling of naturalistic functional MRI time-series during spoken narrative listening.	Language	Encoding
Sacheli et al., 2019. How Task Interactivity Shapes Action Observation.	Motor	Encoding, Violation
Säfström and Domellöf, 2018. Brain activations supporting linking of action phases in a sequential manual task.	Motor	Encoding
Sahyoun et al., 2004. Towards an understanding of gait control: brain activation during the anticipation, preparation and execution of foot movements.	Motor	Encoding
Sali et al., 2020. Neural Mechanisms of Strategic Adaptation in Attentional Flexibility.	Attention	Violation
Sayalı and Badre, 2021. Neural systems underlying the learning of cognitive effort costs.	Cognitive Control	Violation
Saygin et al., 2012. The thing that should not be: predictive coding and the uncanny valley in perceiving human and humanoid robot actions.	Motor	Encoding
Schiffer and Schubotz, 2011. Caudate Nucleus Signals for Breaches of Expectation in a Movement Observation Paradigm.	Motor	Encoding, Violation
Schiffer et al., 2013. Neural changes when actions change: Adaptation of strong and weak expectations.	Motor	Violation
Schiffler et al., 2016. Memory-reliant Post-error Slowing Is Associated with Successful Learning and Fronto-occipital Activity.	Cognitive Control	Violation
Schneider et al., 2018. Disentangling reward anticipation with simultaneous pupillometry / fMRI.	Attention	Encoding
Schuster et al., 2021. Cloze enough? Hemodynamic effects of predictive processing during natural reading.	Language	Encoding, Violation
Schuwerk et al., 2014. Functional activity and effective connectivity of the posterior medial prefrontal cortex during processing of incongruent mental states: MPFC and Incongruent Mental States.	Social Cognition	Violation
Seger et al., 2013. Corticostriatal Contributions to Musical Expectancy Perception.	Music	Violation
Seid-Fatemi and Tobler, 2015. Efficient learning mechanisms hold in the social domain and are implemented in the medial prefrontal cortex.	Social Cognition	Encoding

Seidel et al., 2015. Uncertainty during pain anticipation: The adaptive value of preparatory processes.	Pain	Violation
Seymour et al., 2005. Opponent appetitive-aversive neural processes underlie predictive learning of pain relief.	Pain	Encoding
Sharvit et al., 2018. Modality-specific effects of aversive expectancy in the anterior insula and medial prefrontal cortex.	Pain	Encoding
Sherman et al., 2016. Predictions Shape Confidence in Right Inferior Frontal Gyrus.	Attention	Violation
Sheu and Desmond, 2022. Cerebro-Cerebellar Response to Sequence Violation in a Cognitive Task: an fMRI Study.	Memory	Encoding, Violation
Shin et al., 2014. Neural correlates of social perception on response bias.	Social Cognition	Violation
Singh et al., 2020. The effect of optimistic expectancies on attention bias: Neural and behavioral correlates.	Attention	Encoding, Violation
Sitnikova et al., 2014. Understanding human original actions directed at real-world goals: The role of the lateral prefrontal cortex.	Motor	Violation
Smith et al., 2010. Spatial Attention Evokes Similar Activation Patterns for Visual and Auditory Stimuli.	Attention	Encoding
Söderström et al., 2018. Rapid syntactic pre-activation in Broca's area: Concurrent electrophysiological and haemodynamic recordings.	Language	Violation
Sosic-Vasic et al., 2012. The Modulating Effect of Personality Traits on Neural Error Monitoring: Evidence from Event-Related fMRI.	Cognitive Control	Violation
Stanley and Miall, 2007. Functional activation in parieto-premotor and visual areas dependent on congruency between hand movement and visual stimuli during motor-visual priming.	Motor	Encoding, Violation
Stanley, 2016. Getting to know you: general and specific neural computations for learning about people.	Social Cognition	Encoding, Violation
Stefanics et al., 2019. Feature-specific prediction errors for visual mismatch.	Social Cognition	Encoding, Violation
Stevens et al., 2005. Hemispheric differences in hemodynamics elicited by auditory oddball stimuli.	Attention	Violation
Stewart et al., 2020. Involuntary Orienting and Conflict Resolution during Auditory Attention: The Role of Ventral and Dorsal Streams.	Attention	Violation
Suzuki et al., 2012. Learning to Simulate Others' Decisions.	Social Cognition	Violation

Taylor et al., 1997. Isolation of Specific Interference Processing in the Stroop Task: PET Activation Studies.	Attention	Violation
Tesink et al., 2009. Unification of Speaker and Meaning in Language Comprehension: An fMRI Study.	Language	Encoding, Violation
Thioux and Keysers, 2015. Object visibility alters the relative contribution of ventral visual stream and mirror neuron system to goal anticipation during action observation.	Motor	Violation
Thomas et al., 2018. Where and how our brain represents the temporal structure of observed action.	Motor	Encoding
Thompson and Duncan, 2009. Attentional modulation of stimulus representation in human fronto-parietal cortex.	Attention	Encoding
Thornton et al., 2019. The Social Brain Automatically Predicts Others' Future Mental States.	Social Cognition	Encoding
Tillmann et al., 2003. Activation of the inferior frontal cortex in musical priming.	Music	Violation
Tillmann et al., 2006. Cognitive priming in sung and instrumental music: Activation of inferior frontal cortex.	Music	Violation
Tipper et al., 2015. Body language in the brain: constructing meaning from expressive movement.	Social Cognition	Violation
Trempler et al., 2017. Frontostriatal Contribution to the Interplay of Flexibility and Stability in Serial Prediction.	Cognitive Control	Encoding, Violation
Tune et al., 2016. Sentence understanding depends on contextual use of semantic and real world knowledge.	Language	Encoding, Violation
Uhlmann et al., 2020. Seeing your own or someone else's hand moving in accordance with your action: The neural interaction of agency and hand identity.	Motor	Violation
Van Assche et al., 2014. Functional Dissociations Within Posterior Parietal Cortex During Scene Integration and Viewpoint Changes.	Memory	Encoding
Van Atteveldt et al., 2007. Top–down task effects overrule automatic multisensory responses to letter–sound pairs in auditory association cortex.	Attention	Violation
Van De Meerendonk et al., 2013. Language comprehension interrupted: Both language errors and word degradation activate Broca's area.	Language	Violation
Vanyukov et al., 2019. Neurocomputational mechanisms of adaptive learning in social exchanges.	Social Cognition	Violation
Visalli et al., 2019. Bayesian modeling of temporal expectations in the human brain.	Cognitive Control	Encoding, Violation

Volz et al., 2003. Predicting events of varying probability: uncertainty investigated by fMRI.	Memory	Encoding
Vossel et al., 2015. Cortical Coupling Reflects Bayesian Belief Updating in the Deployment of Spatial Attention.	Attention	Violation
Walter et al., 2020. Self-control and interoception: Linking the neural substrates of craving regulation and the prediction of aversive interoceptive states induced by inspiratory breathing restriction.	Pain	Encoding
Weber et al., 2019. Sentence processing is modulated by the current linguistic environment and a priori information: An fMRI study.	Language	Violation
Wessel et al., 2012. Surprise and Error: Common Neuronal Architecture for the Processing of Errors and Novelty.	Cognitive Control	Violation
Willems et al., 2016. Prediction During Natural Language Comprehension.	Language	Encoding
Wittmann et al., 2005. Reward-Related fMRI Activation of Dopaminergic Midbrain Is Associated with Enhanced Hippocampus-Dependent Long-Term Memory Formation.	Memory	Encoding
Wolf et al., 2014. Emotional valence and spatial congruency differentially modulate crossmodal processing: an fMRI study.	Attention	Violation
Wright et al., 2013. Brain regions concerned with the identification of deceptive soccer moves by higher-skilled and lower-skilled players.	Motor	Violation
Yomogida et al., 2010. The neural basis of agency: An fMRI study.	Social Cognition	Violation
Zhao et al., 2017. Human cortical activity evoked by contextual processing in attentional orienting.	Social Cognition	Violation
Zuanazzi and Noppeney, 2019. Distinct Neural Mechanisms of Spatial Attention and Expectation Guide Perceptual Inference in a Multisensory World.	Attention	Encoding, Violation

Appendix C

The AEROBICS (Analysis & Evaluation of Risk Of Bias in Cognitive Studies) protocol

C.1   Scoring

For each item, read the statement and evaluate whether the related information reported (or not reported) in the paper under investigation may contain potential risk of bias. Select the label (among *low - some concerns - moderate - high*) that best describes the evaluation. In order to formulate an evaluation, consider the principle at the basis of this tool and thus of the evaluation of risk of bias proposed here: risk of bias can be inferred from both the methodology adopted, and the accuracy and specificity of the research protocol, analysis and results' report. The more details are included in the paper pertaining to one item of the present instrument, the more the study protocol adheres to gold standards, the lower the risk of bias. If an item is not applicable to the paper being evaluated, please select the option *Not applicable (N/A)*. If there is no information available about the specific item, please select *High* (where appropriate). At the end convert each label into its numerical equivalent:

- *Low* → 1

- *Some concerns* → 2

- *Moderate* → 3

- *High* → 4

For each domain, sum the scores for the completed items. To calculate the risk-of-bias score for the domain of interest, calculate the quartiles from the maximum score possible in that specific domain and assign a label to the score obtained according to these guidelines:

- I quartile → *Low risk of bias*

- II quartile → *Some concerns on risk of bias*

- III quartile → *Moderate risk of bias*

- IV quartile → *High risk of bias*

For example, if a domain is made up of 10 questions the maximum score possible is 40 and the quartiles, and thus the labels for each risk-of-bias judgment, would be as follows:

- 1-10 → *Low risk of bias*

- 11-20 → *Some concerns on risk of bias*

- 21-30 → *Moderate risk of bias*

- 31-40 → *High risk of bias*

For the overall risk-of-bias judgment, please select the highest level of risk of bias obtained in the single domains.

C.2   Domains & statements

- **Participant selection**:

   1. The control group has been randomly selected and it is clear how it is comparable to/different from the experimental group.

   2. The sample size has been justified with an a priori power analysis (reported with all necessary statistical data) or otherwise.

   3. The sampled population and the recruitment process have been thoroughly described.

   4. The inclusion/exclusion criteria were established before data analysis and are clearly reported in the paper.

   5. If and how participants were compensated is clearly stated in the paper.

   6. For clinical research only, the authors report the diagnostic criteria selected (e.g., DSM-5), the instruments used to corroborate the diagnosis (e.g., SCID-PD), and the specific features of the participants included (e.g., pharmacotherapy, disease duration).

   7. The number of tested participants is reported, alongside the number of exclusions (with the reasons that led to them) and the final sample size.

- **Experimental task**:
   Only for studies including an experimental task

   8. Subjects and/or researchers were blinded to the condition the former were assigned to.

   9. For studies including both an experimental task and a neuropsychological battery, all parts of the study were conducted on the same day.

10. The experimental task is thoroughly described, in sufficient detail that it would be possible to replicate it.

11. The authors describe clearly the characteristics of the stimuli whose manipulation might modulate size of the effect(s) under investigation.

12. All experimental and control conditions are explicitly described, together with procedures to ensure counterbalancing (if needed).

13. The total duration of the experiment, the number and length of breaks, and the number of blocks are reported.

14. The number of practice and experimental trials, the number of stimuli for block, the trial timeline (e.g., inter-stimulus interval, duration of black screen, stimulus duration), and the organization of trials (random, pseudo-random, or fixed) are reported.

15. All variables collected are described and reported in the paper.

16. The authors report the response effector and whether there was any response feedback or response-contingent reward.

– **Support scales**:
Only for studies including (neuro)psychological tests

17. The characteristics of the (neuro)psychological evaluation (e.g., cut-off, scores, reference papers, norm data) are reported in detail.

18. The authors describe thoroughly what the participants are asked to do (i.e., the test).

19. The authors report how the test was administered (e.g., on a lab computer, tablet, online).

20. All variables collected are described and reported (e.g., RTs, accuracy, errors).

21. The response effector and modality are reported.

22. All the tests were done on the same day.

Only for studies including questionnaires

23. The authors describe thoroughly what the participants are asked to do (i.e., the questionnaires).

24. The authors report how the questionnaire was administered (e.g., on a lab computer, tablet, online).

25. The scoring system is clearly explained.

26. The authors report who is asked to answer the questionnaires (participant, parent, caregiver, other).

– **Statistics**

27. A clear description of the statistical method used for all analyses and of the nature of inference (e.g., null hypothesis testing, interval estimation, Bayesian analysis, predictive modeling) is provided.

28. Information relevant for each analysis is reported (e.g., the structure of the models, the methods used for hypothesis testing, the nature of priors for Bayesian analysis, and the nature of any feature selection and cross-validation operations used for machine learning analyses).

29. All dependent and independent variables (including covariates) are reported.

30. Only for online studies, data cleaning procedures (e.g., removal of duplicate or automated bot responses) are reported.

31. An outlier analysis was performed and reported in detail (type, level of the data considered).

32. The exclusion of any trials (e.g., practice trials, errors outliers, too-fast or too-slow responses) and the reasons behind it are reported, together with the total percentage of excluded trials.

33. The handling of missing data is described in detail.

34. In case of multiple comparisons (including subgroup analyses), the correction method for multiple comparisons (e.g., Bonferroni, False Discovery Rate correction) is reported.

35. The analysis and its reporting make it clear how the main hypotheses were tested: an effect size and statistic for each hypothesis tested can be easily extracted from the paper.

36. All the exact main statistics (e.g., F-values for ANOVA, degrees of freedom, r for correlation, Bayes factor for Bayesian analysis) for all tested effects are reported.

Appendix D

Complete ratings of the papers evaluated using the AEROBICS

The complete risk-of-bias ratings for the evaluated papers from the Social Cognition meta-analyses will be reported here. For ease of reading the evaluations provided by the two raters will be listed in two different sections.

For an explanation of the scoring system, the reader is referred to the complete AEROBICS protocol, which can be found in Appendix C.

For complete references, the reader is directed to the Bibliography.

D.1   Rater 1

Reference	Domains				Overall RoB rating
	Participant selection	*Experimental task*	*Support scales*	*Statistics*	
Bardi et al., 2016.	Moderate	Some concerns	N/A	Some concerns	Moderate
Boorman et al., 2013.	Moderate	Some concerns	N/A	Moderate	Moderate
Cassidy and Gutchess, 2015.	Some concerns	Moderate	Some concerns	Moderate	Moderate
Christopoulos and King-Casas, 2015.	Moderate	Some concerns	N/A	Moderate	Moderate
Cloutier et al., 2011.	Moderate	Some concerns	N/A	Some concerns	Moderate
Diaconescu et al., 2017 - Study 1.	Moderate	Some concerns	N/A	Some concerns	Moderate

Diaconescu et al., 2017 - Study 2.	Moderate	Some concerns	N/A	Some concerns	Moderate
Dungan et al., 2016.	Moderate	Some concerns	Moderate	Some concerns	Moderate
Dzafic et al., 2016.	Some concerns	Some concerns	Moderate	Moderate	Moderate

D.2 Rater 2

| | Domains | | | | Overall |
Reference	*Participant selection*	*Experimental task*	*Support scales*	*Statistics*	**RoB rating**
Bardi et al., 2016.	Some concerns	Low	N/A	Some concerns	Some concerns
Boorman et al., 2013.	Some concerns	Low	N/A	Low	Some concerns
Cassidy and Gutchess, 2015.	Some concerns	Some concerns	Some concerns	Some concerns	Some concerns
Christopoulos and King-Casas, 2015.	Moderate	Low	N/A	Some concerns	Moderate
Cloutier et al., 2011.	Moderate	Some concerns	Some concerns	N/A	Moderate
Diaconescu et al., 2017 - Study 1.	Some concerns	Some concerns	N/A	Low	Some concerns
Diaconescu et al., 2017 - Study 2.	Some concerns	Some concerns	N/A	Low	Some concerns
Dungan et al., 2016.	Moderate	Some concerns	Some concerns	Moderate	Moderate
Dzafic et al., 2016.	Some concerns	Low	Moderate	Low	Moderate

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