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Neural decoding of semantic concepts: a systematic literature review

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Abstract

Objective. Semantic concepts are coherent entities within our minds. They underpin our thought processes and are a part of the basis for our understanding of the world. Modern neuroscience research is increasingly exploring how individual semantic concepts are encoded within our brains and a number of studies are beginning to reveal key patterns of neural activity that underpin specific concepts. Building upon this basic understanding of the process of semantic neural encoding, neural engineers are beginning to explore tools and methods for semantic decoding: identifying which semantic concepts an individual is focused on at a given moment in time from recordings of their neural activity. In this paper we review the current literature on semantic neural decoding. *Approach.* We conducted this review according to the Preferred Reporting Items for Systematic reviews and Meta-Analysis (PRISMA) guidelines. Specifically, we assess the eligibility of published peer-reviewed reports via a search of PubMed and Google Scholar. We identify a total of 74 studies in which semantic neural decoding is used to attempt to identify individual semantic concepts from neural activity. *Main results.* Our review reveals how modern neuroscientific tools have been developed to allow decoding of individual concepts from a range of neuroimaging modalities. We discuss specific neuroimaging methods, experimental designs, and machine learning pipelines that are employed to aid the decoding of semantic concepts. We quantify the efficacy of semantic decoders by measuring information transfer rates. We also discuss current challenges presented by this research area and present some possible solutions. Finally, we discuss some possible emerging and speculative future directions for this research area. *Significance.* Semantic decoding is a rapidly growing area of research. However, despite its increasingly widespread popularity and use in neuroscientific research this is the first literature review focusing on this topic across neuroimaging modalities and with a focus on quantifying the efficacy of semantic decoders.

1. Introduction

Our experience of the world has long been regarded by some philosophers as an internal subjective experience that is individual to us [1, 2]. We may have tasted the same apples, smelt the same roses, and heard the same bird song as our neighbours, but our individual mental states have long been thought to have a very distinct and subjective nature [1].

Many philosophers refer to this individual introspective experience as our 'qualia', our own introspectively accessible experience of the world [1, 2]. It has long been considered, by some, to be impossible to know, with absolute certainty, how anyone else experiences the world.

While this may remain true, modern neuroscience is increasingly beginning to reveal how our brains respond to specific experiences within the world. We now know what specific patterns of activity occur in the brain as we eat an apple, or smell a rose, and, broadly speaking, for many people the parts of the brain that become active during these experiences are similar [2–4].

Indeed a significant portion of modern neuroscience is focused on exactly how our conscious mental states as we experience the world (our 'qualia') relate to the activity in our brains [5]. This work has rapidly accelerated in recent years with the development of modern, non-invasive, neuroimaging tools that are capable of observing activity in our brains in real-time [6].

Techniques such as functional magnetic resonance imaging (fMRI) (developed in the 1990s [7, 8]) and electroencephalography (EEG) (developed between the 1870s and 1890s [9], but much more recently coupled with powerful computer-driven statistical analysis techniques) have been combined with studies of neurological aetiologies to revolutionise our understanding of how semantic concepts are encoded in the brain. This new understanding of how our brains encode semantic concepts has given rise to a further field of study, semantic decoding, defined as the decoding of semantic concepts from recordings of our brain activity.

Semantic decoding refers to a combination of hardware and software systems that may be employed to identify the specific semantic concept(s) an individual is focused on, or thinking of, from a recording of their brain activity [10]. It is a technique which opens the doors to a wide range of exciting possibilities and future applications.

In this literature review we review the current state of the art research in semantic decoding methods. We discuss current neuroimaging methods and experimental designs used in semantic decoding and how they may be combined with machine learning pipelines to reveal which specific semantic concepts an individual is focused on. We also discuss the current challenges in this research area, including how to effectively combine multi-modal neuroimaging techniques to more accurately decode semantic concepts and how to develop effective machine learning methods to deal with the typically large, non-stationary, noisy, multi-dimensional datasets involved in this work. Finally, we discuss some current and future applications of this research area.

2. Literature review methods

2.1. Study selection

To review the topic of semantic decoding we followed the Preferred Reporting Items for Systematic reviews and Meta-Analysis (PRISMA) guidelines [11]. We systematically searched within PubMed and Google Scholar databases to identify papers which report neural semantic decoding attempts. The search was run in January 2022 and the search queries used for each database are listed in table 1.

We first removed duplicate results that arose from our four search queries. We then screened the records for their relevance. Specifically, we included papers which described attempts to build and evaluate models that are able to decode the individual discrete semantic concepts an individual participant was focused on at a discrete moment of time from recordings of their neural activity. Consequently, we screened the records according to the criteria set out in table 2.

To further identify additional articles not found by our initial search queries each of the articles shortlisted by applying the screening criteria in table 2 were then inspected. Specifically, the reference list from each article was also screened according to the criteria in table 2. This produced a final list of 74 articles which describe attempts to develop and evaluate neural semantic decoders.

2.2. Definitions

2.2.1. Semantic concepts

At the most basic level a concept is the idea of what something is or how it works and may be held in the mind or expressed in language. Semantics refers to the study of meaning. Thus, a semantic concept may be defined as the meaning of what something is or how it works. This may be distinguished from a perceptual concept, which defines how a concept is perceived (e.g. how it looks or sounds).

Within the field of neuroscience it has been known for some time that different neural systems exist for semantic processing of concepts and perceptual processing of those same concepts [12]. Specifically, early work by Elizabeth Warrington described how patients could match perceptual features of objects without being able to match descriptions of the objects with their names.

More recently, the specific neuro-anatomical basis of these systems have been identified in detail by a series of neuroimaging studies as well as studies of individuals with neurological aetiologies that effect their ability to access semantic memory [13]. Specifically, semantic memory (the process of retrieving semantic information related to a concept) involves a distributed-plus-hub network in which a distributed network of brain regions selectively respond to modality specific features, while a central semantic hub acts to represent semantic similarity between concepts. There is considerable evidence locating this hub within the left hemisphere anterior temporal lobe [13].

A widely supported theory describing how semantic concepts are encoded in the brain is embodiment theory. This states that the meaning of a concept is situated within our experience of the world [14]. So for example, the concept of a tool is situated

Table 1. Search queries used to identify articles relating to neural semantic decoding.

Database	Query
PubMed	((semantic AND decoding) OR (semantic AND prediction) OR (concept AND prediction) OR (concept AND decoding) OR (noun AND prediction) OR (noun AND decoding)) AND ('brain activity' OR neural)
PubMed	((semantic AND decoding) OR (semantic AND prediction) OR (concept AND prediction) OR (concept AND decoding) OR (noun AND prediction) OR (noun AND decoding)) AND (EEG OR electroencephalography OR electroencephalogram OR fMRI OR 'functional magnetic resonance imaging' OR MEG OR 'magnetoencephalogram' OR 'magnetoencephalography' OR fNIRS OR 'functional near infrared spectroscopy' OR ECoG OR 'electrocortiography')
PubMed	((semantic AND decoding) OR (semantic AND prediction) OR (concept AND prediction) OR (concept AND decoding) OR (noun AND prediction) OR (noun AND decoding)) AND ('intracranial EEG' OR iEEG OR 'stereotactic EEG' OR sEEG OR 'invasive EEG' OR 'depth electrodes' OR 'implanted electrodes' OR 'human single-unit' OR 'human single neuron' OR 'concept cells')
Google Scholar	allintitle: (semantic AND decoding AND 'brain activity') OR (semantic AND decoding AND neural) OR (semantic AND decoding) OR (semantic AND prediction AND 'brain activity') OR (semantic AND prediction AND neural) OR (semantic AND prediction) OR (concept AND prediction AND 'brain activity') OR (concept AND prediction AND neural) OR (concept AND prediction) OR (concept AND decoding AND 'brain activity') OR (concept AND decoding AND neural) OR (concept AND decoding) OR (noun AND prediction AND 'brain activity') OR (noun AND prediction AND neural) OR (noun AND prediction) OR (noun AND decoding AND 'brain activity') OR (noun AND decoding AND neural) OR (noun AND decoding)

Table 2. Screening criteria for records returned by search queries.

	Criteria
Include	Report describes an attempt to develop and evaluate, on humans, a model capable of neural semantic decoding.
Include	Clear description of methods and results in terms of decoding accuracy/efficacy.
Include	Report published in a peer reviewed article (journal, conference, or peer-reviewed book chapter).
Exclude	Review, position, theory, and discussion articles.

within our understanding of how tools are used (they are held in the hands, they are used to manipulate other objects, etc). This may be contrasted with other approaches, which state that the meaning of a concept is grounded in abstract symbols or in a universal organisational system [15].

Neuroimaging support for both embodiment theory and the distributed-plus-hub model comes from fMRI studies, which report significant changes in blood flow within both brain regions responsible for percepto-motor circuits during processing of words related to perception of motion and the anterior temporal lobe. For example, processing of words related to tools has been shown to activate the sensori-motor cortex [16].

For the purposes of our review we define a semantic concept as an idea of what something is or how it works that is independent of the perceptual features of the concept such as how it looks or how it sounds.

2.2.2. Semantic encoding and decoding

Semantic encoding may be broadly described as the study of how the brain encodes specific concepts. This includes studying how specific brain regions are involved in the encoding of concepts, as well as exploring how networks of brain regions work together to encode specific semantic concepts [17].

In general, semantic encoding and decoding may be realised by constructing encoding and decoding models [18, 19]. Semantic encoding models are a group of modelling techniques that seek to predict brain activity from stimuli, while semantic decoding models seek to predict the stimuli from neural activity [10].

Both types of model involve the development of signal processing and machine learning pipelines to relate distinct semantic categories to recordings of neural activity. Consequently, these models are frequently confused with one another in the literature [10]. Indeed, encoding and decoding models are often closely related to one another. Although, an encoding model is not a necessary prerequisite of a decoding model, it has two advantages over a decoding model. First, it can in principle provide a complete description of the related encoding process, while a decoding model can provide only a partial description. Second, it can be transformed into an optimal decoding model, a process which is more difficult the other way around [10].

Encoding and decoding models are applicable to a wide range of questions in neuroscience. For example, decoding models have been developed to decode scenes from a TV show viewed by individuals [20], faces seen by individuals [21], pieces of music heard by participants [22], and the quantity of displayed objects [23].

In our review we focus on decoding models applied to the problem of semantic decoding, identifying the single coherent semantic concept an individual is focused on at a given discrete epoch of time from recordings of their neural activity.

3. Results

3.1. Outline

Figure 1 illustrates the process of study selection and the resulting number of identified studies.

A wide range of different neuroimaging tools and methods have been employed by researchers seeking to decode semantic concepts from the brain.

Semantic decoding models seek to identify the discrete semantic concepts an individual is focused on at a given moment in time. Consequently, neural semantic decoding studies start with an experiment that is designed to cue participants to focus their attention on single semantic concepts for discrete periods of time. Neural activity is recorded while participants are cued to pay attention to a single concept. This recorded neural activity is then processed to remove signal noise and increase the signal to noise ratio of key discriminative features. Semantic decoding models are then trained on these features and evaluated in terms of their decoding accuracy.

3.2. Neuroimaging methods

Table 3 enumerates the modalities used in neural semantic decoding studies.

The majority of decoding studies to date have used fMRI. This is due, in large part, to the superior spatial resolution provided by fMRI, which allows whole brain neuroimaging. However, the fMRI does have a number of disadvantages when it comes to studying brain activity related to semantic meaning. Specifically, fMRI has a particularly poor temporal resolution and is only able to detect and monitor changes in oxygenated blood flow (BOLD) that follow electrophysiological neural activity by 2–4 s [98]. Additionally, fMRI is extremely expensive, cumbersome, and requires participants to lie in a confined space in tightly controlled conditions for extended periods of time. Consequently, fMRI studies typically focus on small numbers of participants and are often only able to answer relatively straightforward questions [99].

In contrast, electro-physiological neuroimaging methods, such as EEG or magnetoencephalography (MEG), provide a direct recording of neural activity in mainly cortical neurons with a very high temporal resolution. This provides the potential to explore how semantic encoding patterns change over time [82] at the cost of a considerably poorer spatial resolution.

EEG has been explored as a tool for semantic decoding by a relatively small number of authors and has been demonstrated, in some circumstances, to be able to reveal activity related to processing of a subset of semantic concepts. For example in work by Murphy *et al* [25] differences in EEG correlates of the concepts for 'tools' and 'mammals' were reported to allow a mean decoding accuracy of 72%. Additionally, work by Simanova *et al* [24] reported semantic decoding for the concepts of 'animals' and 'tools' with a mean accuracy of up to 79%.

Two alternative neuroimaging techniques that provide direct recordings of electrophysiological neural activity with the same high temporal resolution as the EEG, while also affording a high spatial resolution and specificity, are macro intracranial electrodes (such as electrocorticogram (ECoG) and stereoelectroencephalography (SEEG)) and micro intracranial electrodes. Macro intracranial electrodes record neural activity from large groups of neurons via a grid of electrodes. This grid is either placed directly on the cortical surface under the skull, in the case of ECoG [100], or can be placed at a wide range of locations in the brain, in the case of SEEG [101]. On the other hand, micro intracranial electrodes allow activity to be recorded from individual neurons at any position in the brain. Consequently, both techniques provide signals with high spatial and temporal resolution that have high signal to noise ratios. However, this comes at the cost of coverage (ECoG and SEEG only cover a limited region of the brain and micro electrodes only allow recordings from a few dozen individual neurons) and with the added risk from the brain surgery that is necessary to implant the electrodes. A set of studies have demonstrated that recordings of ECoG signals, SEEG signals, and micro electrodes may be used for semantic decoding [87–90, 93–97].

In contrast, recent work has demonstrated that it is possible to differentiate semantic concepts from functional near infrared spectroscopy (fNIRS) [79, 80]. For example, recent work by Rybář *et al* [80] reported a mean decoding accuracy of up to 80.9% for differentiating the concepts of 'animals' and 'tools'. fNIRS records levels of oxygenated and de-oxygenated haemoglobin in the cortex by shining an infra-red light through the skull and measuring how the reflected and refracted light changes with blood flow. It measures the same physiological process as fMRI, while allowing participants to sit or move more freely, which enables a wider range of experiment designs at the cost of lower spatial resolution and coverage.

Techniques that record electrophysiological brain activity, such as EEG, provide a direct measure of neural activity as it happens with very high time resolution, whereas blood flow based neuroimaging methods, such as fNIRS, are only able to provide indirect measures of neural activity via changes in the concentration of haemoglobin, a time delayed and spatially imprecise response to electrophysiological

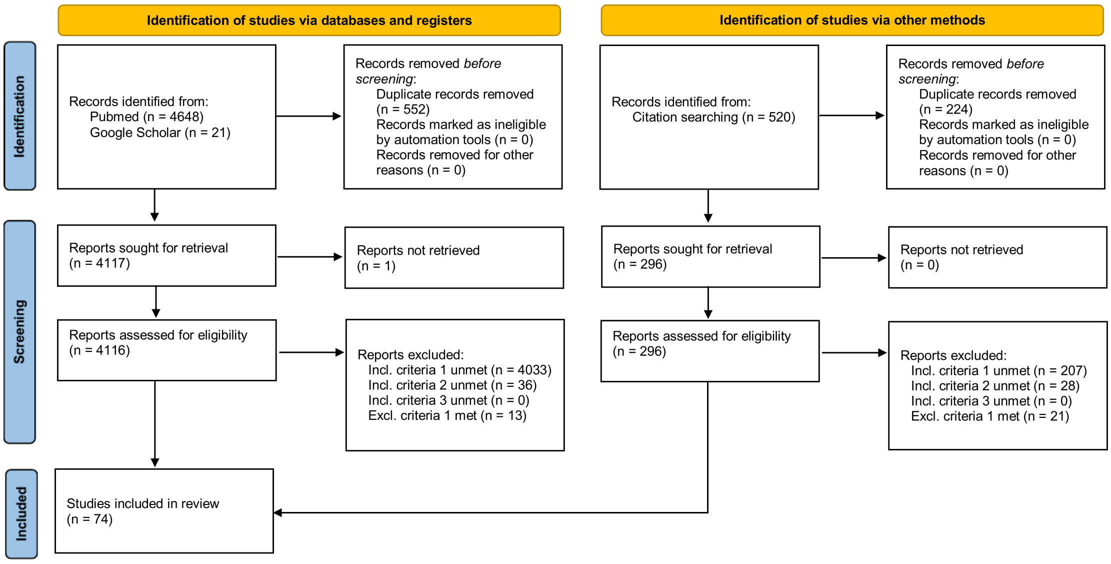

Figure 1. Study selection flowchart.

Table 3. Modalities used for developing neural semantic decoding models.

Modality	No.	References
EEG	5	[24–28]
EEG + MEG	3	[29–31]
EEG + ECoG + SEEG	1	[32]
fMRI	45	[33–77]
fMRI + MEG	1	[78]
fNIRS	2	[79, 80]
MEG	6	[81–86]
Macro electrodes (ECoG, SEEG)	9	[87–95]
Micro electrodes	2	[96, 97]

neural activity [99]. An additional consideration is that non-invasive technology, such as EEG and fNIRS, are relatively cheap and portable, potentially allowing their use in experiments that better capture everyday use of semantic concepts.

However, the considerably poorer spatial resolution of technologies such as EEG and fNIRS presents a significant challenge when compared to technologies that provide a higher resolution recording of brain activity such as fMRI, and this is reflected in the corresponding number of semantic decoding publications that make use of each technique. This is because different semantic concepts can be spatially encoded throughout the brain, including in subcortical regions [72] which can be observed by fMRI but, conventionally, are harder to measure with scalp based measurement technologies [102].

Indeed, work by Murphy and Poesio suggests that the ability to identify semantic concepts from the EEG is closely related to the ease with which the associated neural activity may be identified from electrophysiological recordings of cortical brain activity (EEG and MEG). For example, the concepts of 'tools' and 'mammals' are differentiable from EEG data alone [25] and fMRI neuroimaging work by Pulvermüller *et al* [16] has shown these two concepts involve activations in the sensorimotor and parietal cortices, which are cortical regions observable via EEG. Conversely, other semantic concepts that are, perhaps, more complex in nature (e.g. such as specific foods or 'hunger') have been shown to involve subcortical brain areas, making them potentially considerably harder to identify via current non-invasive neuroimaging techniques [72].

3.3. Open datasets

A small proportion of the neuroimaging datasets that have been recorded during studies developing and evaluating neural semantic decoders have been made publicly available, allowing other research groups to re-use datasets to develop and evaluate new methods. We list publicly available datasets for developing and evaluating neural semantic decoders in table 4. We also list which study originally recorded the dataset and other studies which have made use of the same dataset.

Note, a number of studies (such as [52, 71, 91, 94]) make use of datasets recorded in other studies but not made publicly available. This is typically because the studies were conducted within the same lab and re-used data that was available in the lab but not publicly available. A small number of studies make use of data that is described as being available on request, either to eligible researchers [38], or to all [45, 82]. However, these datasets are not published. Finally, one study by Carlson *et al* used data that is described in the study as publicly available [63]. However, on further investigation the data was found to no longer be publicly available because the archive site was taken down due to lack of funding. We do not include these datasets in table 4.

Table 4. Publicly available datasets for developing and evaluating semantic decoding models.

Modality	Available at	Reported	Re-used in
ECoG	http://klab.tch.harvard.edu/resources/liuetal_timing 3.html#sthash.BiYFH24Z.dpbs	[88]	[89]
ECoG	https://purl.stanford.edu/xd109qh3109	[92]	
Micro electrodes	https://github.com/rebrowski/abstractRepresentations InMTL	[97]	
EEG	www.cs.cmu.edu/~tom/science2008/	[72]	[69]
fMRI	https://openneuro.org/datasets/ds000105/versions/ 00001	[75]	[43]
fMRI	https://datadryad.org/stash/dataset/doi:10.5061/dryad. vmcvdncpf	[49]	
fMRI	www.cs.cmu.edu/~tom/science2008/	[72]	[65, 69]

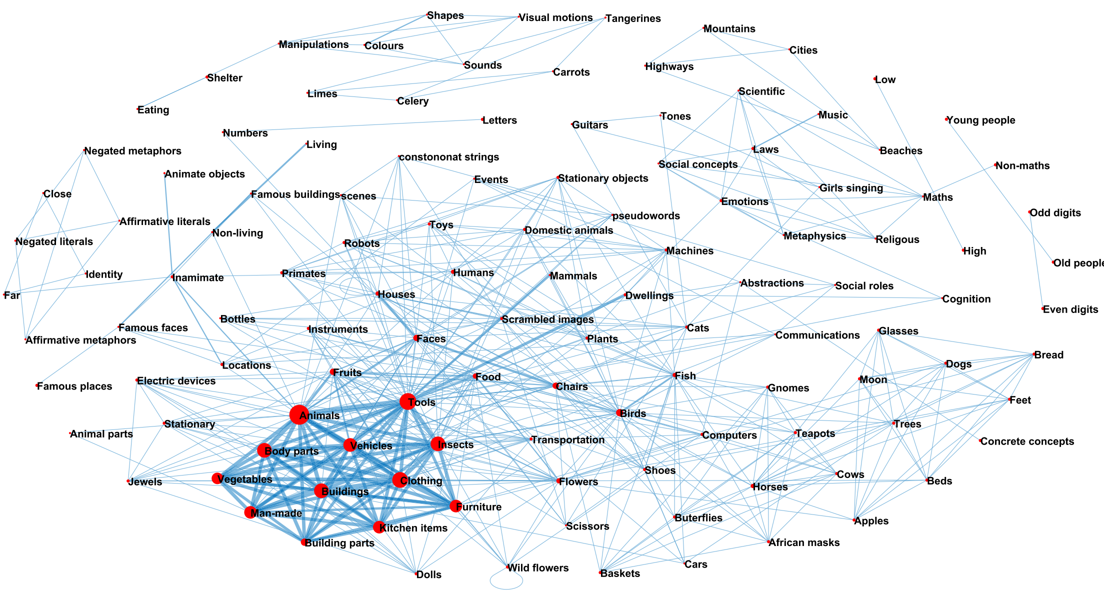

Figure 2. Semantic categories that neural semantic decoders have been developed to differentiate. The size of the nodes is proportional to the number of studies that have investigated a particular category, while the width of the edges between nodes is proportional to the number of studies that have reported attempts to build decoders to differentiate particular pairs of concepts. Note, the positions of the concepts in the network diagram are arbitrary.

3.4. Experimental design

The experimental design is probably the most important set of decisions to make when attempting semantic decoding. Here, we review three crucial elements of experimental design: semantic concepts and categories, mental tasks, and stimulus or cue presentation.

3.4.1. Semantic concepts and categories

The semantic categories that neural semantic decoders have been trained to differentiate vary from study to study. However, there are some groups of semantic categories that are frequently used to train and evaluate neural semantic decoders. Figure 2 illustrates which pairs of semantic categories semantic neural decoders have been developed to differentiate. Specifically, we illustrate a network on semantic categories where each node represents an individual category and each edge represents an attempt to build a decoder to differentiate those categories. The size of the nodes is proportional to the number of studies that report attempts to build decoders that recognise that category, while the widths of the edges between pairs of nodes are proportional to the number of studies that report attempts to differentiate those pairs of categories.

The most frequently differentiated semantic categories include animals and tools [24, 35, 38, 42, 65, 67, 69, 72, 80, 81, 93], tools and buildings [42, 65, 67, 69, 72, 81], and animals and body parts [28, 42, 65, 67, 69, 72, 79, 81]. Several studies have also shown that it is possible to differentiate more than two semantic categories at a time [59, 60, 65, 67, 69, 85].

There is a relatively dense network of semantic categories that are frequently decoded, including tools, buildings, body parts, and animals. However, it is important to note that this may not necessarily indicate that these specific concepts are easier to decode than other concepts, as many authors opt to replicate and extend the work of other authors, particularly when selecting which categories to attempt to decode.

We also identified a set of studies focused on differentiating individual concepts within a single category [36, 38, 40, 72, 79, 81], for instance, physics concepts [40], sets of 180 words [39], and sets of 240 sentences [73]. We did not include these studies in figure 2 to avoid over-complicating the illustration.

The selection of semantic categories and concepts is occasionally not clearly justified and only a few studies have focused on this problem in detail. Several studies used concepts based on previous research. For instance, Bauer *et al* [37] used concepts based on a previous behavioural study that collected pairwise dissimilarity ratings. While, a small number of studies employed a data-driven strategy to generate the concepts or the semantic categories. For instance, Pereira *et al* [39] partitioned a semantic vector space, which was used to encode individual concepts (see section 3.5), by a clustering method and a core concept was selected from each region.

3.4.2. Tasks

A wide variety of different mental tasks have been used in semantic decoding studies to date. These are enumerated in table 5. They all share the common goal of encouraging participants to hold a target concept in their minds, while at the same time many aim to also test participants focus during the experiment.

In the 'silent naming' task [25, 29, 31, 49, 76, 80], participants are asked to silently name, in their minds, a semantic concept. An alternative, related task, is the 'aloud naming' task [31, 59, 83, 87, 90] in which participants name the concept aloud. This task has the advantage that participant responses can be recorded.

Many studies [33, 34, 36, 37, 40–42, 46, 56, 60, 62, 65, 67, 69, 72] asked participants to think of the same properties of the semantic concept in each experimental trial. Each participant was asked to come up with a set of properties for each concept before the start of the experiment. Several studies [49, 87] restricted the properties to various sensory and motor properties. A study by Zinszer *et al* [79] removed the constraint of generating the properties before the experiment and let participants think freely about the meaning of the given concept or any memory it evoked. Conversely, a study by Bauer and Just [58] asked participants to think about features of animals that they had been taught about thus far. Pereira *et al* [39] asked participants to think about the meaning of the concept in the given context (in a sentence, with an accompanying image, or with accompanying concepts). While, a study by Rybář *et al* [80] restricted the imagery modalities to three different tasks in which participants were asked to visualize the concept in their minds, imagine the sounds made by the concept, and imagine the feeling of touching the concept (a concrete object). Additionally, a study by Reddy *et al* [68] asked participants to vividly imagine detailed mental images as similar as possible to preseen images.

In a work by Anderson *et al* [53, 71], participants were asked to imagine a situation that they individually associated with the concept. Some related research focused on more complex concepts or scenarios described by sentences, typically one sentence was presented one word (or phrase) at a time and participants were asked to think about the meaning of each phrase as it appeared and then the overall meaning of the sentence [45, 54, 61, 66, 73]. For more information in this direction, see related research on encoding or decoding of episodic recollection and autobiographical memory [103–111], or procedural knowledge [112].

In several studies [24, 27, 28, 35, 47], participants were presented with target and non-target semantic categories and asked to respond upon the appearance of items from the non-target (or target) category, for instance, by pressing a mouse button. While, in some studies [82, 85, 88, 89], participants were asked to press a button if any image repeated itself consecutively (1-back task) to ensure that participants were paying attention. Studies by a few researchers [51, 75, 95] used a 1-back match task in which participants were asked to judge whether the category matched the category presented immediately before. Studies by Carlson *et al* [63] and Niazi *et al* [77] used delay matching in which participants indicated which choice of stimulus matched the target stimuli presented previously. Additionally, a study by Alizadeh *et al* [26] asked participants to remember all six elements presented in a sequence.

Other studies rather focused on other semantic aspects of the concepts. For example, in a study by Sudre *et al* [81], participants answered semantic yes/no questions for concrete nouns (e.g. 'Was it ever alive?', 'Can you pick it up?'). In a study by Chan *et al* [30], participants responded based on a size judgement of the concept, i.e. smaller or larger than 0.3 meters in any dimension, while in a study by Miller *et al* [92] the orientation of an image stimuli was used as a form of oddball task. Studies by Fernandino *et al* [55, 64] asked participants whether the stimulus, either a word or a pseudoword, referred to something that can be experienced through the senses. In a study by Wei *et al* [87], participants were instructed to name a concept that was closest to the one shown in the picture. While, Kivisaari *et al* [38] provided three verbal clues for each concept (e.g. 'has 4 legs', 'is found in the savannah', 'has a trunk') and participants attempted to identify the concept. In a study by Simanova *et al* [84], participants were asked to internally produce a word in the cued semantic category with the initial cued letter. Dehghani *et al* [52] conducted a study in which participants were asked to read a story and then answer a comprehension question. Similarly, in a study by Mahon and Caramazza [57], participants were asked to judge the conceptual

Table 5. Mental tasks used by the semantic decoding studies. Note, some studies employ two or more task types and, therefore, appear in two or more rows.

Task type	Specific task	References
Naming	Silent naming task	[25, 29, 31, 49, 76, 80]
	Aloud naming task	[31, 59, 83, 87, 90]
Properties	Silent properties generation (think about a consistent pre-generated set of properties)	[33, 34, 36, 37, 40–42, 46, 56, 60, 65, 67, 69, 72]
	Think about sensory and motor properties of the concept	[49, 87]
	Think about taught features	[58]
	Think about characteristics of the concept	[62]
Meaning	Think freely about meaning of stimulus or evoked memories	[79]
	Contextual meaning reflection (think about the meaning of the concepts in the given context)	[39, 91, 94]
	Think about associated situation with the concept	[53, 71]
	Contextual meaning reflection (think about overall meaning of a sentence/phrase)	[45, 54, 61, 66, 73, 74]
	Read story then answer comprehension question	[52]
Imagery	Visual imagery, auditory imagery, tactile imagery	[80]
	Generate detailed mental images as similar as possible to pre-seen images	[68]
Category/property recognition	Out-of-category recognition	[24, 27, 35]
	In-category recognition	[28, 47]
	Yes/no questions	[81]
	Size judgement	[30]
	Orientation judgement	[92]
	Category specific judgement	[32, 96, 97]
	Answer whether it can be directly experienced with senses	[55, 64]
	Concept similarity judgment (scale 1–4)	[57]
	Semantic similarity of 2 words to a key word	[48]
	Semantic congruity judgment	[70]
	Name the colour of the object or the background	[83]
	Silently name a word from a cued category with a cued initial letter	[84]
	Oddball task	[62, 78, 82, 86, 93]
	1-back task	[82, 85, 88, 89]
	1-back match task	[51, 75, 95]
	Delayed matching	[63, 77]
	Remember all six elements presented in a sequence	[26]
Object recognition	Name an object that was closest to the one shown in the picture	[87]
	Object identification + naming	[38]
Passive	Passive task	[31, 43, 44, 50, 63]

similarity of two objects on a scale from 1 to 4, while Wang *et al* [48] asked participants to judge which of two words was most similar to a key word. In a study by Li *et al* [70], participants were asked to silently judge semantic congruity of the presented stimuli with a cued category. Finally, in a study by Honari-Jahromi *et al* [83] participants were asked to name the colour of the object or the background (in images).

However, several studies used passive tasks, for instance, passive viewing of images [43, 63], passive reading [50], and passive listening [31, 44]. It has been shown that the viewed object can be identified from the passive viewing of images [113–118], which is the focus of the field of image retrieval. The same argument applies for instance for speech production and passive listening. For this reason, passive tasks alone may not be sufficient to allow semantic decoding. To mitigate this issue and ensure participants attention, several studies [62, 78, 82, 86, 93] included an oddball task in which participants were asked to respond, typically by pressing a button, when a different type of stimulus was presented.

3.4.3. Stimulus/cue

The stimulus modalities used to cue participants to focus on a particular semantic category are enumerated in table 6.

The most common stimuli type used is a visual image presentation modality, which 41 studies used. Stimuli included photographs (grey-scale or

Table 6. Stimulus presentation modalities used by the semantic decoding studies.

Modality	References
Image	[24, 25, 28, 29, 35, 36, 43, 46, 47, 54, 59, 63, 67, 70, 75, 77, 78, 80, 82, 83, 85, 87–89, 92, 93, 95–97]
Image + written caption	[32–34, 39, 58, 65, 69, 72, 74, 81]
Image + auditory (speech)	[34, 79]
Auditory (speech)	[24, 27, 30, 31, 35, 38, 51, 57, 68, 94]
Auditory (natural sounds)	[35, 44]
Written word	[24, 26, 30, 31, 35, 37, 40–42, 46, 48, 49, 53, 55, 56, 60, 62, 64, 71, 84, 90, 91]
Written text or phrases	[39, 45, 50, 52, 54, 61, 66, 73, 86]

coloured) or line drawings of the concepts the participants were instructed to focus on. In 12 studies written captions or spoken words were added to the images. Written words or text, presented all at once or each word one by one, were the second most used modality and were employed by 31 studies. Spoken words (or speech) and natural sounds were used less often and were employed in only 12 studies.

A concern when using cues to instruct participants to focus on particular categories is that the presentation of the stimulus may introduce potential processing-related confounds into the classification process. For instance, focusing on a concept while seeing its image raises the question of what is used for the differentiation between different concepts: the visual processing of the image (low-level perceptual features), the imagination of the concept, or some combination of brain activities related to both processes. Some studies explicitly analysed the influence of some of these possible confounds. For instance, Murphy *et al* [25] examined brightness, mean spatial frequency, and visual complexity of the stimuli images. However, the set of potential confounds and methods (for instance, how to measure image complexity) has not been comprehensively studied. An alternative method is to use only certain brain regions or networks in the analysis, typically excluding visual areas [39]. However, this approach is only feasible for neuroimaging techniques with good spatial resolution, such as fMRI, intracranial electrodes, or ECoG. The separation of the task and stimulus presentation can potentially avoid this issue, see also the related field of mental imagery [118–123]

3.5. Feature extraction

Depending on the recording modality, a wide variety of features can be used for semantic decoding. In fMRI and fNIRS, signals are typically epoched from 4 up to 9 s after the stimulus onset to account for the haemodynamic delay in event-related designs. EEG, MEG, and intracranial electrode recordings are traditionally analysed in the temporal domain (e.g. ERP analysis), the frequency domain to reveal the signal power distribution over frequencies, or the time-frequency domain for varying spectral activities over time.

Apart from these traditional features, studies have started to utilize domain-specific multi-dimensional information in which each concept is encoded by 'semantic features' that are not acquired from the recordings. The two main approaches used can be categorized as attribute-based views and vector space models of semantics, see also a recent review [124].

In the attribute-based view, a concept can be encoded according to its semantic attributes or features. Each attribute is assigned a value or a set of values related to its probability, weight, or importance [125–129]. A study by Sudre *et al* in MEG [81] used a semantic knowledge base consisting of 218 interpretable semantic attributes. This dataset was collected by asking 218 questions to a group of Amazon Mechanical Turk users about the semantic properties of 1000 concrete nouns [81, 130]. For example, some questions were related to size, shape, surface properties, context, and typical usage, with answers on a scale of 1–5, and then rescaled to a range of −1 to 1. In particular, they employed a two-stage classifier with a layer of intermediate semantic features between the input features and the class label. While, Fernandino *et al* [55, 64] used a semantic model based on five semantic attributes directly related to sensory-motor processes: sound, colour, shape, manipulability, and visual motion. Ratings for these attributes on a scale from 0 to 6 were collected for 900 words.

In another example, Anderson *et al* [66] used an experiential attribute model with 65 attributes [126] that modelled semantic representation using people's ratings of their association with different attributes of experience on a scale of 0–6. Collected attributes spanned sensory, motor, affective, spatial, temporal, causal, social, and abstract cognitive experiences. Lastly, a study by Wang *et al* [73] developed a set of 42 concept-level semantic features. These binary features included information from categories such as the perceptual and affective characteristics of an entity (e.g. whether it was man-made, size, colour, temperature, positive affective valence, and high affective arousal), animate beings (person, human-group, animal), and time and space properties (e.g. unenclosed setting, change of location). For example, the noun 'judge' was encoded with the following features: person, social norms, knowledge, and communication. The study used an encoding regression model to determine the mapping between 42 semantic features as well as 6 thematic role markers of phrases in sentences and neural activation patterns assessed with fMRI.

In vector space models of semantics, automated methods can be used to learn semantic features from the statistical properties of words and phrases in large text corpora [131–135]. Computational linguistics has shown that contextual information provides a good approximation to word meaning [136–139]. Mitchell *et al* [72] developed a model to learn predictive relationships between the statistics of word co-occurrences (with a set of 25 verbs in a large text corpus) and fMRI neural activation patterns (BOLD activation patterns). Zinszer *et al* [79] used representational similarity-based neural decoding to test whether semantic information of words and pictures represented by textual co-occurrence frequency in large text corpora is encoded in fNIRS.

More recently, word2vec [133, 140] and GloVe [134] have become popular semantic spaces [135, 141]. In word2vec, semantic vector representations are learnt in a way that a word can be predicted given the average semantic vector of the other words in the context (e.g. 5 words before and 5 words after the word of interest). In GloVe, representations are created in a way that the dot product of two vectors equals the logarithm of the probability of the associated words co-occurring in text. For instance, Pereira *et al* [39] used GloVe to decode individual word meanings in fMRI while participants were instructed to think about the meaning of a target word in the given context (either in a sentence, with an accompanying image or accompanying words). Djokic *et al* [50] investigated processing of literal and metaphoric sentences in fMRI using GloVe, a visual model, and a compositional model. While, Kivisaari *et al* [38] used word2vec to decode a semantic concept in fMRI while participants read brief verbal descriptions of the target concept. Participants received clues about individual concepts in the form of three isolated semantic features, given as verbal descriptions. Dehghani *et al* [52] used an extension of word2vec for paragraph vectors to decode specific stories participants were reading in fMRI. Honari-Jahromi *et al* [83] used word2vec to investigate neural representations of words within phrases in MEG.

3.6. Feature selection

Nowadays, multivariate analyses methods, such as multivariate pattern analysis (MVPA) in fMRI literature, utilizing information from multiple channels (voxels in fMRI, electrodes in EEG, etc) are dominant, while historically many studies used to apply univariate analyses methods to the semantic decoding problem. Feature selection methods are thus typically needed to decrease the number of features from inherently high-dimensional neuroimaging data. Furthermore, feature selection methods may be used to attempt to address inter-person differences in neural encoding.

A basic method is to restrict the neuroimaging data, for instance to certain channels, time points, or frequencies. For example, the analysis

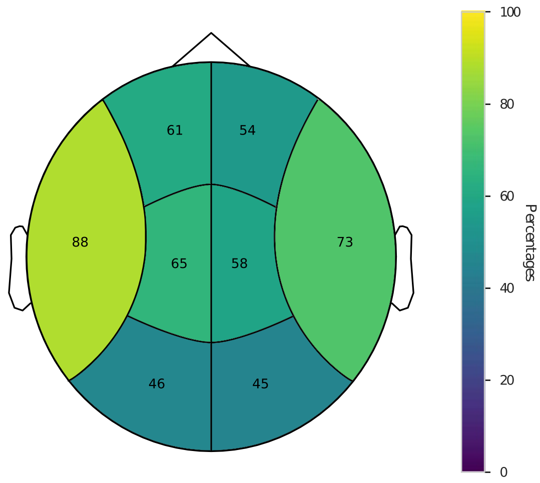

Figure 3. Illustration of the most informative brain lobes for the semantic decoding. Values represent percentages from the number of studies that reported this information, typically inspected in a post-analysis (see the supplementary material available online at stacks.iop.org/JNE/19/021002/mmedia). Left and right frontal, parietal, temporal, and occipital lobes were chosen for a broad overview, which could be useful for a wide range of neuroimaging modalities including EEG and fNIRS decoding.

can be performed on anatomically defined regions of interest or to repeat the analysis on small local areas (searchlight analysis in fMRI literature). Many studies [36–38, 40, 72, 73, 79] attempt to select the most stable channels over presentations of concepts within a participant. While, some studies [40, 73] have applied a two-level hierarchical factor analysis to select brain locations over multiple participants.

We illustrate which regions of the brain are most commonly used in semantic neural decoding studies in figure 3. Specifically, we coarse grain the brain regions into eight regions: frontal, parietal, temporal, and occipital brain regions in the left and right hemispheres. We then illustrate the percentage of neural semantic decoding studies which make use of information from each region.

It can be seen that the left temporal lobe is most frequently used as the basis for extracting features for semantic decoding. This is not a surprising result as the left temporal lobe of the brain has been widely reported to be involved in conceptual naming [142] and, as we saw in section 3.4.2, naming tasks are used in several studies, while, as we saw in section 3.4.3, many studies use written or spoken concept names to present concepts to study participants. Furthermore, the anterior temporal lobe is well-known to be the hub, within the distributed-plus-hub model, for semantic memory retrieval in the brain [13, 143].

Statistical-based feature selection methods making use of the category labels can also be used. For instance, some studies [33, 34, 50] used channel selection based on ANOVA. Alternatively, supervised machine learning can be used to drive the channel selection.

Dimensionality reduction methods that project the data into a smaller subspace are popular. For example, principal component analysis projects the data into a space with components that successively maximize the variance of the projected data, independent component analysis decomposes the data into statistically independent components, and common spatial patterns [144, 145] (used to aid binary classification) projects the data into a space that maximizes the signal variance for one class, while simultaneously minimizing the signal variance for the opposite class. These projections are then followed by a selection of only a certain number of dimensions, typically the ones that describe the most useful aspects of the data. It is important to note this decomposition can be spatial (over channels), temporal (over time), spectral (over frequencies), or any combination of these dimensions.

3.7. Machine learning models

Machine learning methods are used within semantic decoding to identify the specific semantic concept(s) an individual is focused on from a recording of their brain activity. Thus, the core aim of the machine learning part of the semantic decoding process is to categorise and classify recordings of brain activity into labels describing the associated semantic concepts.

Machine learning methods may, in general, be grouped into two distinct categories: unsupervised methods and supervised methods.

Unsupervised machine learning methods do not make use of any underlying category labels in order to process the data. Thus, they are best suited to aiding the categorisation process by, for example, reducing the dimensionality of the feature space. However, they cannot, by themselves, be used to classify data [146, 147].

Supervised machine learning methods, by contrast, make use of category labels in order to attempt to identify rules by which the data may be classified [146, 147]. For example, supervised machine learning methods may be used to identify rulesets or thresholds to separate neural feature sets into their associated semantic category labels.

Table 7 enumerates the machine learning classifiers used for semantic decoding. The most frequently used machine learning methods were support vector machines, naive Bayes classifiers, and regression based methods. Somewhat surprisingly, we have not found semantic decoders to date that make use of deep learning methods such as convolutional neural networks or long short-term memory networks [148]. This is despite the rapid recent growth of the use of these methods in many related domains of neuroscience [149]. We anticipate that semantic decoding studies that use these advanced machine learning methods will begin to appear in the near future.

Table 7. Machine learning classifiers used by the semantic decoding studies. Note, some studies employ two or more classifiers and, therefore, appear in two or more rows.

Method	References
Support vector machine	[25–27, 29, 30, 35, 37, 44, 49, 51, 54, 58, 62, 65, 67, 68, 70, 76, 87, 88, 90, 91, 94, 97]
Logistic regression	[24, 33, 34, 41, 48, 77, 80, 84]
Naive Bayes	[28, 36, 40, 42, 45–47, 56, 60, 61, 65, 87]
Regression	[38, 39, 52, 55, 61, 64, 66, 72, 73, 81, 83, 86, 93]
Linear discriminant analysis	[63, 76, 78, 82, 85, 92, 96]
K-nearest neighbours	[31, 59, 65, 89]
Neural network	[43, 53, 74, 89]
Correlation-based	[50, 57, 69, 71, 75, 79, 95]

3.8. Measuring performance

The final step of any decoding pipeline is to evaluate the decoding performance. When only a few classes are being distinguished, standard machine learning evaluation methods can be used for binary or multi-class classification problems, such as classification accuracy, F1 score, Cohen's kappa, or preferably a confusion matrix.

With an increasing number of classes to distinguish, the above methods do not tell us the whole picture, for instance, the class may be incorrectly predicted but it would be the second choice of a multi-class classifier or it may be semantically similar to the true class (if this makes sense in the application context). In these cases, several studies used rank accuracy [36, 37, 39–42, 45, 55, 56, 58, 60, 61, 67, 72, 73], which is defined as the percentile rank of the correct class in the classifier's rank output. The list of predicted classes is rank-ordered from most to least likely and the normalized rank of a correct class in a sorted list is computed. Rank accuracy ranges from 0 to 1 and the chance level performance is 0.5.

Several studies used leave-two-out pairwise comparison [38, 39, 52, 63, 69, 71, 72, 75, 79, 81–83, 86]. This procedure leaves two samples s_1 and s_2 for testing during cross-validation. With two classes C_1 and C_2, it compares two predicted classes and decides which order is a better match whether ($s_1 = C1$ and $s_2 = C_2$) or ($s_1 = C_2$ and $s_2 = C_1$). The chance level performance is 0.5. For two samples and two classes, this is mathematically equivalent to the area under the curve measure. However, this metric makes comparisons between studies difficult unless more information is provided. Furthermore, performance measured this way is not appropriate for many real-world use-case scenarios where only two samples could be predicted and it does not consider the same class for the two samples. To make this issue more confusing, several studies incorrectly refer to this procedure as leave-two-out cross-validation. Whereas, from a machine learning perspective, leave-two-out cross-validation leaves two samples from the training and then classifies each sample separately to which class it belongs (from all possible classes). On a related note, a small number of studies only reported mean or individual pairwise accuracies from multi-class classification (e.g. from one-vs-one or one-vs-rest strategies) without trying to aggregate them together. Nevertheless, we must acknowledge that the main research focus of many studies, presented here, was on localization of brain regions involved in semantic decoding or encoding. Thus, not all reported performance metrics are useful when attempting to compare decoding accuracy between studies.

Overall, the selection of the evaluation metrics ultimately depends on the application scenario. We strongly suggest reporting everything necessary, such as confusion matrices, so that one can compute any other metric of interest, whenever this is feasible. Nevertheless, it is important to note that these metrics do not represent the whole picture of the approach used. This issue is similar to the issue of the information transfer rate (ITR) metric, which is a popular metric in brain–computer interface (BCI) systems (see section 5.3) and measures the amount of information in bits that is conveyed by a system's output within a given time [150–152] (see equation (2) in section 3.9). Whereas, in real-case BCI scenarios, users' states, such as fatigue and perceived ease of use of the BCI must also be taken into consideration.

3.9. Decoding performance

We compare semantic decoding performance between studies. Due to differences in reporting metrics used in different studies we are unable to compare performance of all the studies in our review. However, to make at least a partial comparison, we decided to use ITR to compare decoding performance. ITR incorporates the number of classes the semantic decoder is attempting to differentiate, the time taken to decode the concepts, and the reported decoding accuracy. It is defined, in [153], by:

$$B = log_2\, C + p\, log_2 p + (1-p)\, log_2 \left(\frac{1-p}{C-1}\right), \quad (1)$$

$$\mathrm{ITR} = B \times \left(\frac{60}{T}\right), \quad (2)$$

where C denotes the number of classes, p denotes the classification accuracy, and T denotes the time taken to make a selection in seconds.

Thus, it allows meaningful comparisons of decoding performance to be made between semantic decoding studies, even when different numbers of semantic categories and/or different time windows are employed. For comparison, consider the case where studies are compared in terms of accuracy, or some similar metric such as area under the curve. Such a comparison is only meaningful when the number of classes and the time windows are the same across studies. For example, an accuracy of 50% may be good when there are four different classes, but could be no better than random chance when there are only two classes.

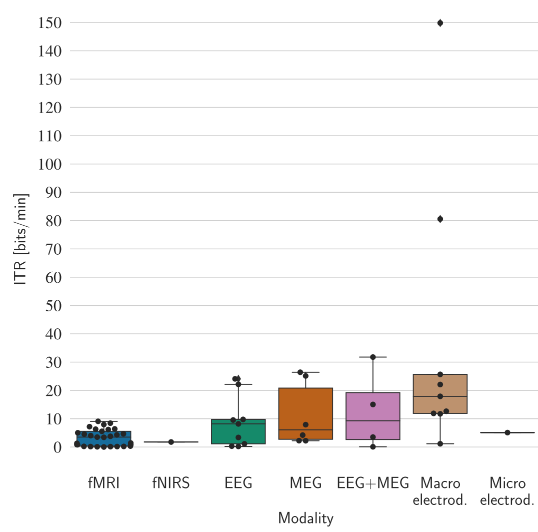

Figure 4. Information transfer rate (ITR) in bits per minute for semantic decoding studies, for which it was possible to calculate ITR (see the supplementary material). Macro electrod. indicates macro intracranial electrodes such as ECoG or SEEG, while Micro electrod. indicates micro intracranial electrodes used for single unit recordings.

Figure 4 shows ITRs in bits per minute for studies that reported decoding accuracies. Nevertheless, this information represents an optimistic view. To compute ITR, we ignored inter-stimulus intervals in experimental paradigms and instead only used the end of the time window after the stimulus onset which was used for classification. It is important to note that all studies were conducted offline. In real-time semantic decoding applications, ITR would most probably be significantly lower.

As expected, neuroimaging techniques affected by a slow haemodynamic delay, such as fMRI and fNIRS, require longer times and thus they typically have lower ITRs (in a range from 0.02 to 9.08) in comparison with electro-physiological neuroimaging methods (with ITRs in a range from 0.09 to 149.83), even though they typically achieve greater accuracies. Indeed, if performance is measured without taking into account the length of the time window needed by the decoder for each of the neuroimaging modalities, fMRI would out-perform scalp based measures such as EEG. However, given the rapidity with which human thought can switch between semantic concepts we consider it appropriate to incorporate the length of the time window into our comparison of decoder performance.

It is worth noting that ITR is not a perfect metric for comparing semantic decoding studies as it does not take into account the semantic similarity of concepts. For example, pairs of concepts that are semantically unrelated to one another are likely to be much easier to decode than concepts that are closely related. This can be seen in figure 2, which shows that categories that are quite distinct from one another, such as 'animals' and 'tools', are frequently used in semantic decoding studies, whereas more similar concepts, such as 'celery' and 'carrots', are rarely used. An ideal metric for measuring the performance of semantic decoders would also incorporate some measure of the semantic similarity of the concepts that were decoded. However, as semantic similarity between concepts varies across languages, cultures, and even individuals, such a measure could prove challenging to develop and is beyond the scope of our review.

4. Key challenges

Semantic neural decoding has considerable potential to aid understanding of how concepts are held and processed in the brain. However, it is first necessary to overcome current gaps in our understanding of how the brain works. For example, more accurate characterisation of activity patterns in terms of location, timing, and morphology has the potential to enable more accurate semantic neural decoding.

It is also necessary to improve current machine learning methods used to identify semantic concepts from neural data. This may include using joint recording methods, such as simultaneous EEG and fMRI to improve the accuracy of semantic decoding.

An additional challenge is identifying the most appropriate combinations of methods to differentiate specific sets of semantic concepts and determine which methods may be employed for particular applications. For example, fMRI may be used to differentiate a wide range of different semantic concepts, but is impractical for many possible applications of semantic decoding (for example, building a practical semantic communication device, see section 5.3).

It is also important to note that the specific concepts that semantic decoders are able to differentiate currently depends largely on the neuroimaging methods employed. In general we observed that decoders that used techniques with higher spatial resolution—such as fMRI or intracranial electrodes—were better able to decode concepts that are more semantically similar to one another than neuroimaging techniques with lower spatial resolution, such as EEG or fNIRS. Advances in signal processes techniques for the EEG and fNIRS may help to close this gap in future, but it is likely to remain the case that a higher spatial resolution is needed to more accurately decode more semantically similar concepts.

Finally, differences in inter-participant and inter-language neural encodings of semantic concepts represent a considerable challenge [33]. Ideally, one would wish to build a decoding model from one subgroup of individuals and be able to apply this with any new individual.

However, neural signatures of semantic encoding vary considerably across individuals and even across experiments with the same individual [99]. There are a variety of reasons for this. In particular neuroanatomical differences between individuals mean that direct one-to-one mappings of neural encoding patterns for a given semantic concept between participants are not possible [99]. In addition, non-stationarity in neural representations of meaning results in differences in neural encoding patterns between experimental sessions with the same participant [154].

Some of these differences can be corrected for by pre-processing the recorded neural data. For example, fMRI recordings can be fit to common templates via a series of warping and translation steps to provide some degree of neuroanatomical homogeneity, at the cost of reduced spatial precision and resolution [155]. However, conceptual organisation of semantic concepts differs between individuals as different people relate concepts to one another quite differently. For example, while one individual may relate the concept of 'celery' to the concept of 'hunger' another may not. These differences in conceptual organisation result, according to embodiment theory, in differences in neuroanatomical localisation of encoding patterns for concepts. Consequently, even with correct inter-person neuro-anatomical alignment there may still be considerable differences in encoding patterns between individuals. Methods to address this include searching for signatures of semantic concepts within neural data [156] or joint feature ranking selection [33]. For example, joint feature ranking identifies signatures of concepts across different neuro-anatomical structures and localisations by searching for temporal dynamic modulations of neural activity that co-vary with presentations of specific semantic concepts.

An additional consideration is differences in neural encoding of semantic concepts by individuals who speak different languages. A semantic concept may be, to some extent, independent of language; the concept of 'food' (for example) is a universal one. However, the way specific concepts are encoded in our brain is determined by multiple factors including, but not limited to, mappings to other related concepts, and societal and cultural views of the concept. Moreover, the meaning of concepts can change over the life span [157].

Emerging evidence suggests a mixed picture, with some similarities in neural representations reported (e.g. [158, 159]). However it is not certain that these similarities will generalise well across all languages. Therefore, inter-participant/language differences (e.g. in neuro-anatomical structure, as well as in structuring of neural encoding) need to be accounted for when attempting to understand semantic encoding or build semantic decoding models [99]. Methods have been developed to attempt to help overcome these differences, such as hyper-alignment analysis [154] or mutual similarity relationships [156, 160].

5. Current and future applications and directions

Semantic decoding allows the identification of the specific semantic concept(s) an individual is presented with or focused on at a given moment in time. This emerging field of research suggests many application areas.

5.1. Tools for neuroscience

Semantic decoding has the potential to provide a useful toolset to neuroscientists seeking to investigate how our brains store, relate, and process semantic concepts. For example, the multivariate pattern analysis method used in some semantic decoding studies has also been widely used to understand which brain regions are involved in representing semantic concepts [161]. Semantic decoding has also been used to build and test models of memory re-consolidation after receiving further, refining, information from input sentences [162].

A more specific example of this is the use of semantic decoding to explore neural representations of naturalistic stimulus complexity in the early visual and auditory cortices. A recent neuroscientific study by Güçlütürk *et al* [163] used semantic decoding methods to identify how complex natural stimuli are encoded in these parts of the brain.

Other researchers have used tools developed for semantic decoding to explore how concepts at different 'levels' are encoded in our brains. For example, early work by Rosch *et al* [164] defined a 'basic level' concept upon which other more complex concepts may be constructed. For example, Rosch defined a 'bird' as a basic level concept while more specific concepts (such as 'robin' or 'crow') exist at subordinate levels in this hierarchy.

This early conceptual framework has been shown, via the application of semantic decoding tools, to map to specific organisational structures for semantic encoding in the brain. For example, work by Bauer and Just [41] showed that 'basic level' concepts occupied more spatially distributed neural encoding patterns, while subordinate level concepts occupied less widely distributed, more concentrated brain areas.

This, in turn, relates to the distributed-plus-hub model of semantic memory retrieval in the brain. Under this model, visual, perceptual, and motor related features of individual concepts involve a distributed network of brain regions located within the brain regions responsible for the associated cognitive processes [13]. So for example, the concept of 'tools' is likely to be associated with motor-related cognitive processes and involves a distributed network that includes the motor cortex. This distributed network is then bound together in a central amodal hub, located within the anterior temporal lobe, which is responsible for relating semantic concepts to one another. So, for example, basic level and more complex concepts are related to one another in the anterior temporal lobe and semantic decoding studies can aid understanding of this process.

5.2. Clinical applications

The ability to accurately decode and classify concepts from recordings of brain activity has potential clinical applications in treating disease. An early review in this area suggested that many of the computational and neuroimaging techniques developed for semantic neural decoding could be employed to classify brain disorders such as schizophrenia and depression [165].

This approach was shown to be usable in the diagnosis of developmental dyscalculia in a small study with 13 individuals with dyscalculia and 36 control participants [166]. A time-resolved multivariate analysis method was used to analyse fMRI recorded from participants while they judged the correctness of multiplication results. The results showed detailed differences between the groups, indicating that neural decoding techniques could be adopted for clinical diagnosis in future.

Following on from this early work, neural decoding techniques have also been applied to attempt to understand and treat aphasia [167]. Aphasia is a disorder of language that results from damage to the brain and causes deficits in the production and/or comprehension of speech. Pasley and Knight [167] suggested that neural decoding of semantic concepts could be used to understand how semantic encoding is affected by aphasia. Furthermore, they suggested that, during attempted treatment of aphasia, semantic decoding could be used to judge the effectiveness of the treatment. Treatments could then be adjusted according to this neural measure of their efficacy.

Semantic neural decoding has also been shown to be able to differentiate between individuals with schizophrenia and healthy controls [168]. Specifically, a multivariate state space model was used to analyse the representations of mental processes of individuals as they performed the Sternberg Item Recognition Paradigm [169]. Significant differences were found between controls and individuals with schizophrenia, suggesting a possible further clinical application.

More recently, neural decoding techniques have been shown, in two separate studies, to be able to differentiate between individuals with autism and control participants [170, 171].

Another recent exciting example of this is the suggestion that neural decoding of semantic concepts may be used as a potential test for Alzheimer's disease [172].

Alzheimer's disease is a progressive neurodegenerative disease that leads to gradual loss of cognitive function and, in many cases, ultimately leads to death. One of the symptoms of Alzheimer's disease is a loss of semantic knowledge that begins years before the onset of dementia [173] and it has been suggested that this early loss of semantic knowledge could be used as an early test for Alzheimer's disease. Specifically, it was suggested in [172] that the semantic neural decoding methods, developed in fMRI studies and extended to use with other neural imaging technologies, could be deployed as a test for Alzheimer's disease.

However, there are considerable challenges that first need to be overcome before this potential application can be realised. Specifically, the relationships between semantic knowledge decline and specific Alzheimer's disease pathologies needs to be more thoroughly investigated.

As a final example, neural decoding has also been demonstrated to allow identification of individuals who are engaged in suicidal ideation. Specifically, a fMRI study by Just *et al* [174] was used to identify neural signatures related to the concepts of 'death', 'cruelty' and other concepts related to suicide in 17 suicidal ideators and 17 controls. Significant differences in neural encoding patterns for these concepts allowed differentiation of these groups with a 91% accuracy, suggesting semantic decoding could potentially be used to identify individuals at risk of suicide.

5.3. Communication aids

The possibility to accurately decode the concept an individual is focused on also suggests an application as a communication aid; specifically, as a unique form of BCI.

BCIs have been proposed as a technological solution to aid communication [175, 176]. They can be intuitive and easy to use [177–180]. However, the current communication speeds and accuracies achievable with BCIs are relatively low when compared to other communication platforms [179, 180]. Indeed, most current BCIs achieve communication rates (speeds and accuracies) of around 27 bits per minute [153, 181], while eye trackers can achieve communication rates of around 41 bits per minute [182] and human speech is typically between 160-190 words per minute [183, 184] making BCIs for communication only really useful when other interfaces are not feasible [185].

One of the key limits to communication speed in BCI systems stems from the serial communication paradigm, which forms a part of the basis of all BCI systems, and indeed the majority of assistive technologies used to aid with communication. Specifically, communication proceeds 1 bit at a time and, as a consequence of this, virtually all efforts to improve BCI bit rates have focused on simply increasing the speed at which serial input may be made with the BCI [181, 186–192]. Indeed, even the relatively new research area of hybrid BCIs [193] uses serial communication, albeit with the occasional possibility to enter two commands together [194].

Semantic decoding could be employed to achieve a form of parallel communication with BCI, improving their communication speed considerably. For example, identifying the multi-bit semantic concept of 'hunger' directly from neural data could be much faster than spelling out 'I–A–M–H-U-N-G-R-Y' in series via a current state-of-the-art BCI.

Some work in the field of BCI is already moving in this direction. For example, the use of a single shot decoding attempts to identify the concept an individual is focused on is one of the first attempts in BCI to deploy semantic decoding techniques as a communication paradigm [38, 81, 195, 196].

Related BCIs have been developed based on semantic relations. Geuze *et al* [197] introduced a BCI based on EEG to determine which prime word a user had in mind. Users were presented with a probe word, the BCI detected whether the word is related to the prime word, and a new probe word was chosen from an association network. This process was repeated until a certain confidence threshold was met. An average decoding accuracy of 38% was reported using 100 probes and 150 possible words. Additionally, Wenzel *et al* [198] used a combination of EEG and eye gaze. Users looked for words belonging to a semantic category of interest from a stream of words on the screen. The online BCI detected whether the words were subjectively relevant to the category. An average rank for the category of interest among the five categories was 1.62 after a hundred words had been read.

Some related research focuses on identification of cognitive concepts from neural signals in 'cognitive BCIs' [199]. However, these cognitive BCIs make use of implanted electrodes (a technology which fundamentally limits their utility due to the inherent safety and ethical concerns entailed in such an approach), and are not based on semantic concepts, but rather the broader concept of 'cognitive states' (which includes emotions, intention, executive function, motor commands, etc) [199].

Asides from this work, a small amount of work has also been conducted in ECoG based BCIs [87] that seek to identify semantic concepts. However, this also comes with the same impracticalities as cognitive BCIs. Additionally, a small number of studies have attempted to provide control for users by identifying the semantic concepts 'yes' or 'no' responses [200]. However, the results of these attempts have been inconclusive (even when conducted with fMRI [201]).

The use of semantic decoding for communication may be interpreted as a semiotic system [202]. Indeed, BCIs have been interpreted as semiotic translation systems that translate intention to action [203], wherein the link between intention, brain activity, and resulting action can be expressed within a semiotic framework. By linking intention, brain activity, and action to specific semantic concepts in the mind semantic decoding has the potential to allow this interpretation to be made more explicit.

5.4. Other applications and privacy concerns

Finally, the ability to identify the specific semantic concept an individual is focused on, or thinking of, has numerous other potential applications that, to date, have only been briefly suggested in the literature.

One such application is the use of neural decoding in the field of 'neuromarketing'. This field suggests the use of neuroscientific techniques to develop, refine, and test marketing strategies for commercial products, for example by measuring neural signature of affective (emotional) responses to particular products [204].

Semantic decoding methods may be used to identify which specific concepts an individual focuses on when shown advertising material. This could, in turn, be used to identify more effective advertising strategies.

However, applications such as this and other similar possible uses of semantic decoding suggest the need to consider the privacy and ethical issues raised by semantic decoding [6]. Specifically, neural decoding offers the possibility to decode and interpret a part of an individual current mental state. This could, theoretically, be done without the permission of the individual, for example as a part of a criminal investigation.

The associated privacy and ethical issues are rarely considered in the majority of the literature on semantic neural decoding, perhaps because the technology is currently at a very early stage where such applications feel a long way off. However, one recent discussion paper [205] begins to consider these issues and develops an evaluation framework to consider issues of privacy and ethics in the field of neural decoding. We anticipate considerably more discussion on these issues as the field develops further.

6. Discussion and conclusions

We systematically sought records of studies that attempted to develop semantic neural decoders. Our search methodology included searches of PubMed records and Google Scholar and included all relevant peer reviewed articles that we could identify on these databases. However, no literature review can ever be completely comprehensive and we may have neglected to include some records that describe semantic neural decoders, either because the title and abstract did not indicate that this was attempted in the study, or because we misunderstood the title and abstract and incorrectly excluded the paper. Thus, while our review considers the majority of semantic neural decoding studies it may not be comprehensive. Nevertheless, we are able to draw some key conclusions from our analysis of this literature.

Specifically, the majority of neural semantic decoders make use of the fMRI to record neural data, while a smaller number of studies use other methods such as EEG or MEG. The range of concepts that these decoders attempt to identify is relatively large but there is a core subset of concepts (such as animals and tools) that are very frequently decoded. Experimental designs vary considerably across studies with a wide range of different types of cues and experimental tasks used. On the other hand the range of machine learning methods used by semantic decoders is relatively modest, comprised largely of support vector machines and regression based methods.

The relationship between semantic encoding models and decoding models is not always consistently described in the literature. Indeed some studies confuse these two terms and present an encoding study as a decoding study or visa-versa. We have endeavoured to only include studies that present semantic decoding models in this review. However, an important caveat is that some encoding models are constructed in such a way that adapting the model to achieve semantic decoding would be extremely trivial. Indeed, in some cases an encoding model is also, in effect, a decoding model because the predicted encoding maps the model identifies are explicitly linked to discrete semantic concepts. In such cases we have included the study in our review.

Understanding how our brains encode semantic concepts is an important goal in modern neuroscientific research and enables many new and exciting areas of research. Not least amongst these is the rapidly developing area of semantic decoding, the attempt to develop processing pipelines and decoding models to identify the specific semantic concept an individual is focused on from recordings of their brain activity.

We have identified several key methods employed to tackle the challenge of semantic decoding. Although there are many challenges inherent in developing and evaluating effective models, semantic decoding has the potential to identify, sometimes with quite high levels of accuracy, the specific concept an individual is focused on. This may, in future, enable a wide range of applications such as new clinical diagnostic tests or fast and accurate communication aids.

Data availability statement

All data that support the findings of this study are included within the article (and any supplementary files).

Conflict of interest

The authors declare they have no competing interests.

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References

[1] Velmans M 2002 *Understanding Consciousness* (London: Taylor and Francis)
[2] Blumenfeld H 2016 Neuroanatomical basis of consciousness *The Neurology of Conciousness* (New York: Academic) pp 3–29
[3] Mahon B Z and Caramazza A 2009 Concepts and categories: a cognitive neuropsychological perspective *Annu. Rev. Psychol.* **60** 27–51
[4] Vigliocco G, Vinson D P, Druks J, Barber H and Cappa S F 2011 Nouns and verbs in the brain: a review of behavioural, electrophysiological, neuropsychological and imaging studies *Neurosci. Biobehav. Rev.* **35** 407–26
[5] Mormann F and Koch C 2007 Neural correlates of consciousness *Scholarpedia* **2** 1740
[6] Haynes J-D and Rees G 2006 Decoding mental states from brain activity in humans *Nat. Rev. Neurosci.* **7** 523–34
[7] Ogawa S, Lee T M, Nayak A S and Glynn P 1990 Oxygenation-sensitive contrast in magnetic resonance image of rodent brain at high magnetic fields *Magn. Reson. Med.* **14** 68–78
[8] Belliveau J, Kennedy D, McKinstry R, Buchbinder B, Weisskoff R, Cohen M, Vevea J, Brady T and Rosen B 1991 Functional mapping of the human visual cortex by magnetic resonance imaging *Science* **254** 716–9
[9] Swartz B E 1998 The advantages of digital over analog recording techniques *Electroencephalogr. Clin. Neurophysiol.* **106** 113–7
[10] Naselaris T, Kay K, Nishimoto S and Gallant J 2011 Encoding and decoding in fMRI *NeuroImage* **56** 400–10
[11] Moher D, Liberati A, Tetzlaff J, Altman D G and Group T P 2009 Preferred reporting items for systematic reviews and meta-analyses: the PRISMA statement *PLoS Med.* **6** b2535
[12] Warrington E K and Shallice T 1984 Category specific semantic impairments *Brain* **107** 829–53
[13] Patterson K, Nestor P J and Rogers T T 2007 Where do you know what you know? The representation of semantic knowledge in the human brain *Nat. Rev. Neurosci.* **8** 976–87
[14] Meteyard L, Cuadrado S R, Bahrami B and Vigliocco G 2012 Coming of age: a review of embodiment and the neuroscience of semantics *Cortex* **48** 788–804
[15] Murphy G 2002 *The Big Book of Concepts* (Cambridge, MA: MIT Press)
[16] Pulvermüller F 2005 Opinion: brain mechanisms linking language and action *Nat. Rev. Neurosci.* **6** 576–82
[17] Van Uden C E, Nastase S A, Connolly A C, Feilong M, Hansen I, Gobbini M I and Haxby J V 2018 Modeling semantic encoding in a common neural representational space *Front. Neurosci.* **12** 437
[18] Kragel P A, Koban L, Barrett L F and Wager T D 2018 Representation, pattern information and brain signatures: from neurons to neuroimaging *Neuron* **99** 257–73
[19] Kriegeskorte N and Douglas P K 2019 Interpreting encoding and decoding models *Curr. Opin. Neurobiol.* **55** 167–79
[20] Vodrahalli K *et al* 2018 Mapping between fMRI responses to movies and their natural language annotations *NeuroImage* **180** 223–31
[21] Li Y, Richardson R M and Ghuman A S 2017 Multi-connection pattern analysis: decoding the representational content of neural communication *NeuroImage* **162** 32–44
[22] Hoefle S, Engel A, Basilio R, Alluri V, Toiviainen P, Cagy M and Moll J 2018 Identifying musical pieces from fMRI data using encoding and decoding models *Sci. Rep.* **8** 2266
[23] Bulthé J, De Smedt B and de Beeck H P O 2014 Format-dependent representations of symbolic and non-symbolic numbers in the human cortex as revealed by multi-voxel pattern analyses *NeuroImage* **87** 311–22
[24] Simanova I, van Gerven M, Oostenveld R, Hagoort P and Vandenberghe R 2010 Identifying object categories from event-related EEG: toward decoding of conceptual representations *PLoS One* **5** e14465
[25] Murphy B, Poesio M, Bovolo F, Bruzzone L, Dalponte M and Lakany H 2011 EEG decoding of semantic category reveals distributed representations for single concepts *Brain Lang.* **117** 12–22
[26] Alizadeh S, Jamalabadi H, Schönauer M, Leibold C and Gais S 2017 Decoding cognitive concepts from neuroimaging data using multivariate pattern analysis *NeuroImage* **159** 449–58
[27] Correia J M, Jansma B, Hausfeld L, Kikkert S and Bonte M 2015 EEG decoding of spoken words in bilingual listeners: from words to language invariant semantic-conceptual representations *Front. Psychol.* **6** 71
[28] Behroozi M, Daliri M R and Shekarchi B 2016 EEG phase patterns reflect the representation of semantic categories of objects *Med. Biol. Eng. Comput.* **54** 205–21
[29] Murphy B and Poesio M 2010 Detecting semantic category in simultaneous EEG/MEG recordings *Proc. NAACL HLT 2010 1st Work. Comput. Neurolinguistics* (Association for Computational Linguistics) pp 36–44
[30] Chan A M, Halgren E, Marinkovic K and Cash S S 2011 Decoding word and category-specific spatiotemporal representations from MEG and EEG *NeuroImage* **54** 3028–39
[31] Suppes P, Lu Z-L and Han B 1997 Brain wave recognition of words *Proc. Natl Acad. Sci.* **94** 14965–9
[32] Morton N W, Kahana M J, Rosenberg E A, Baltuch G H, Litt B, Sharan A D, Sperling M R and Polyn S M 2013 Category-specific neural oscillations predict recall organization during memory search *Cereb. Cortex* **23** 2407–22
[33] Akama H, Murphy B, Lei M and Poesio M 2014 Cross-participant modelling based on joint or disjoint feature selection: an fMRI conceptual decoding study *Appl. Inform.* **1** 1
[34] Akama H, Murphy B, Na L, Shimizu Y and Poesio M 2012 Decoding semantics across fMRI sessions with different stimulus modalities: a practical MVPA study *Front. Neuroinform.* **6** 24
[35] Simanova I, Hagoort P, Oostenveld R and van Gerven M A J 2014 Modality-independent decoding of semantic information from the human brain *Cereb. Cortex* **24** 426–34
[36] Shinkareva S, Mason R, Malave V, Wang W, Mitchell T and Just M 2008 Using FMRI brain activation to identify cognitive states associated with perception of tools and dwellings *PLoS One* **3** e1394
[37] Bauer A J and Just M A 2019 Brain reading and behavioral methods provide complementary perspectives on the representation of concepts *NeuroImage* **186** 794–805
[38] Kivisaari S L, van Vliet M, Hultén A, Lindh-Knuutila T, Faisal A and Salmelin R 2019 Reconstructing meaning from bits of information *Nat. Commun.* **10** 927

[39] Pereira F, Lou B, Pritchett B, Ritter S, Gershman S, Kanwisher N, Botvinick M and Fedorenko E 2018 Toward a universal decoder of linguistic meaning from brain activation *Nat. Commun.* **9** 963
[40] Mason R A and Just M A 2016 Neural representations of physics concepts *Psychol. Sci.* **27** 904–13
[41] Bauer A J and Just M A 2017 A brain-based account of 'basic-level' concepts *NeuroImage* **161** 196
[42] Just M, Cherkassky V, Aryal S and Mitchell T 2010 A neurosemantic theory of concrete noun representation based on the underlying brain codes *PLoS One* **5** e8622
[43] Hanson S J, Matsuka T and Haxby J V 2004 Combinatorial codes in ventral temporal lobe for object recognition: Haxby (2001) revisited: is there a 'face' area? *NeuroImage* **23** 156–66
[44] De Martino F, Valente G, Staeren N, Ashburner J, Goebel R and Formisano E 2008 Combining multivariate voxel selection and support vector machines for mapping and classification of fMRI spatial patterns *NeuroImage* **43** 44–58
[45] Yang Y, Wang J, Bailer C, Cherkassky V and Just M A 2017 Commonalities and differences in the neural representations of English, Portuguese and Mandarin sentences: when knowledge of the brain-language mappings for two languages is better than one *Brain Lang.* **175** 77–85
[46] Shinkareva S V, Malave V L, Mason R A, Mitchell T M and Just M A 2011 Commonality of neural representations of words and pictures *NeuroImage* **54** 2418–25
[47] Coutanche M N and Thompson-Schill S L 2015 Creating concepts from converging features in human cortex *Cereb. Cortex* **25** 2584–93
[48] Wang J, Baucom L B and Shinkareva S V 2013 Decoding abstract and concrete concept representations based on single-trial fMRI data *Hum. Brain Mapp.* **34** 1133–47
[49] Soto D, Sheikh U A, Mei N and Santana R 2020 Decoding and encoding models reveal the role of mental simulation in the brain representation of meaning *R. Soc. Open Sci.* **7** 192043
[50] Djokic V G, Maillard J, Bulat L and Shutova E 2020 Decoding brain activity associated with literal and metaphoric sentence comprehension using distributional semantic models *Trans. Assoc. Comput. Linguist.* **8** 231–46
[51] Ghio M, Vaghi M M S, Perani D and Tettamanti M 2016 Decoding the neural representation of fine-grained conceptual categories *NeuroImage* **132** 93–103
[52] Dehghani M *et al* 2017 Decoding the neural representation of story meanings across languages *Hum. Brain Mapp.* **38** 6096
[53] Anderson A J, Murphy B and Poesio M 2014 Discriminating taxonomic categories and domains in mental simulations of concepts of varying concreteness *J. Cogn. Neurosci.* **26** 658–81
[54] Kumar M, Federmeier K D, Fei-Fei Li and Beck D M 2017 Evidence for similar patterns of neural activity elicited by picture- and word-based representations of natural scenes *NeuroImage* **155** 422–36
[55] Fernandino L, Humphries C J, Conant L L, Seidenberg M S and Binder J R 2016 Heteromodal cortical areas encode sensory-motor features of word meaning *J. Neurosci.* **36** 9763–9
[56] Buchweitz A, Shinkareva S V, Mason R A, Mitchell T M and Just M A 2012 Identifying bilingual semantic neural representations across languages *Brain Lang.* **120** 282–9
[57] Mahon B Z and Caramazza A 2010 Judging semantic similarity: an event-related fMRI study with auditory word stimuli *Neuroscience* **169** 279–86
[58] Bauer A J and Just M A 2015 Monitoring the growth of the neural representations of new animal concepts *Hum. Brain Mapp.* **36** 3213
[59] Van de Putte E, De Baene W, Brass M and Duyck W 2017 Neural overlap of L1 and L2 semantic representations in speech: a decoding approach *NeuroImage* **162** 106–16
[60] Vargas R and Just M A 2020 Neural representations of abstract concepts: identifying underlying neurosemantic dimensions *Cereb. Cortex* **30** 2157–66
[61] Just M A, Wang J and Cherkassky V L 2017 Neural representations of the concepts in simple sentences: concept activation prediction and context effects *NeuroImage* **157** 511–20
[62] Sheikh U A, Carreiras M and Soto D 2021 Neurocognitive mechanisms supporting the generalization of concepts across languages *Neuropsychologia* **153** 107740
[63] Carlson T A, Schrater P and He S 2003 Patterns of activity in the categorical representations of objects *J. Cogn. Neurosci.* **15** 704–17
[64] Fernandino L, Humphries C J, Seidenberg M S, Gross W L, Conant L L and Binder J R 2015 Predicting brain activation patterns associated with individual lexical concepts based on five sensory-motor attributes *Neuropsychologia* **76** 17–26
[65] Behroozi M and Daliri M R 2014 Predicting brain states associated with object categories from fMRI data *J. Integr. Neurosci.* **13** 645–67
[66] Anderson A J, Binder J R, Fernandino L, Humphries C J, Conant L L, Aguilar M, Wang X, Doko D and Raizada R D S 2017 Predicting neural activity patterns associated with sentences using a neurobiologically motivated model of semantic representation *Cereb. Cortex* **27** 4379–95
[67] Chang K M K, Mitchell T and Just M A 2011 Quantitative modeling of the neural representation of objects: how semantic feature norms can account for fMRI activation *NeuroImage* **56** 716–27
[68] Reddy L, Tsuchiya N and Serre T 2010 Reading the mind's eye: decoding category information during mental imagery *NeuroImage* **50** 818
[69] Anderson A J, Zinszer B D and Raizada R D 2016 Representational similarity encoding for fMRI: pattern-based synthesis to predict brain activity using stimulus-model-similarities *NeuroImage* **128** 44–53
[70] Li Y *et al* 2011 Reproducibility and discriminability of brain patterns of semantic categories enhanced by congruent audiovisual stimuli *PLoS One* **6** e20801
[71] Anderson A J, Kiela D, Clark S and Poesio M 2017 Visually grounded and textual semantic models differentially decode brain activity associated with concrete and abstract nouns *Trans. Assoc. Comput. Linguist.* **5** 17–30
[72] Mitchell T M, Shinkareva S V, Carlson A, Chang K-M, Malave V L, Mason R A and Just M A 2008 Predicting human brain activity associated with the meanings of nouns *Science* **320** 1191–5
[73] Wang J, Cherkassky V L and Just M A 2017 Predicting the brain activation pattern associated with the propositional content of a sentence: modeling neural representations of events and states *Hum. Brain Mapp.* **38** 4865
[74] Polyn S M, Natu V S, Cohen J D and Norman K A 2005 Category-specific cortical activity precedes retrieval during memory search *Science* **310** 1963–6
[75] Haxby J V, Gobbini M I, Furey M L, Ishai A, Schouten J L and Pietrini P 2001 Distributed and overlapping representations of faces and objects in ventral temporal cortex *Science* **293** 2425–30
[76] Cox D D and Savoy R L 2003 Functional magnetic resonance imaging (fMRI) 'brain reading': detecting and classifying distributed patterns of fMRI activity in human visual cortex *NeuroImage* **19** 261–70
[77] Niazi A M, van den Broek P L, Klanke S, Barth M, Poel M, Desain P and van Gerven M A 2014 Online decoding of object-based attention using real-time fMRI *Eur. J. Neurosci.* **39** 319–29
[78] Brandman T and Peelen M V 2017 Interaction between scene and object processing revealed by human fMRI and MEG decoding *J. Neurosci.* **37** 7700–10
[79] Zinszer B D, Bayet L, Emberson L L, Raizada R D S and Aslin R N 2017 Decoding semantic representations from functional near-infrared spectroscopy signals *Neurophotonics* **5** 1

[80] Rybář M, Poli R and Daly I 2021 Decoding of semantic categories of imagined concepts of animals and tools in fNIRS *J. Neural Eng.* **18** 046035

[81] Sudre G, Pomerleau D, Palatucci M, Wehbe L, Fyshe A, Salmelin R and Mitchell T 2012 Tracking neural coding of perceptual and semantic features of concrete nouns *NeuroImage* **62** 451–63

[82] Proklova D, Kaiser D and Peelen M V 2019 MEG sensor patterns reflect perceptual but not categorical similarity of animate and inanimate objects *NeuroImage* **193** 167–77

[83] Honari-Jahromi M, Chouinard B, Blanco-Elorrieta E, Pylkkänen L and Fyshe A 2021 Neural representation of words within phrases: temporal evolution of color-adjectives and object-nouns during simple composition *PLoS One* **16** e0242754

[84] Simanova I, van Gerven M A J, Oostenveld R and Hagoort P 2015 Predicting the semantic category of internally generated words from neuromagnetic recordings *J. Cogn. Neurosci.* **27** 35–45

[85] Contini E W, Goddard E and Wardle S G 2021 Reaction times predict dynamic brain representations measured with MEG for only some object categorisation tasks *Neuropsychologia* **151** 107687

[86] Fyshe A, Sudre G, Wehbe L, Rafidi N and Mitchell T M 2019 The lexical semantics of adjective–noun phrases in the human brain *Hum. Brain Mapp.* **40** 4457–69

[87] Wang W, Degenhart A D, Sudre G P, Pomerleau D A and Tyler-Kabara E C 2011 Decoding semantic information from human electrocorticographic (ECoG) signals *2011 Annual Int. Conf. IEEE Engineering in Medicine and Biology Society* vol 2011 (IEEE) pp 6294–8

[88] Liu H, Agam Y, Madsen J R and Kreiman G 2009 Timing, timing, timing: fast decoding of object information from intracranial field potentials in human visual cortex *Neuron* **62** 281–90

[89] Jahromy F Z and Daliri M R 2017 Semantic category-based decoding of human brain activity using a Gabor-based model by estimating intracranial field potential range in temporal cortex *J. Integr. Neurosci.* **16** 419–28

[90] Na Y, Choi I, Jang D P, Kang J K and Woo J 2019 Semantic-hierarchical model improves classification of spoken-word evoked electrocorticography *J. Neurosci. Methods* **311** 253–8

[91] Schrouff J, Mourão-Miranda J, Phillips C and Parvizi J 2016 Decoding intracranial EEG data with multiple kernel learning method *J. Neurosci. Methods* **261** 19

[92] Miller K J, Schalk G, Hermes D, Ojemann J G and Rao R P 2016 Spontaneous decoding of the timing and content of human object perception from cortical surface recordings reveals complementary information in the event-related potential and broadband spectral change *PLoS Comput. Biol.* **12** e1004660

[93] Vidal J R, Ossandón T, Jerbi K, Dalal S S, Minotti L, Ryvlin P, Kahane P and Lachaux J P 2010 Category-specific visual responses: an intracranial study comparing gamma, beta, alpha and ERP response selectivity *Front. Hum. Neurosci.* **4** 195

[94] van de Nieuwenhuijzen M E, Axmacher N, Fell J, Oehrn C R, Jensen O and van Gerven M A 2016 Decoding of task-relevant and task-irrelevant intracranial EEG representations *NeuroImage* **137** 132–9

[95] Sabra Z, Bonilha L and Naselaris T 2020 Spectral encoding of seen and attended object categories in the human brain *J. Neurosci.* **40** 327

[96] Kraskov A, Quiroga R Q, Reddy L, Fried I and Koch C 2007 Local field potentials and spikes in the human medial temporal lobe are selective to image category *J. Cogn. Neurosci.* **19** 479–92

[97] Reber T P, Bausch M, Mackay S, Boström J, Elger C E and Mormann F 2019 Representation of abstract semantic knowledge in populations of human single neurons in the medial temporal lobe *PLoS Biol.* **17** e3000290

[98] Glover G H 2011 Overview of functional magnetic resonance imaging *Neurosurg. Clin. North Am.* **22** 133–9

[99] Akama H and Murphy B 2017 Emerging methods for conceptual modelling in neuroimaging *Behaviormetrika* **44** 117–33

[100] Miller K J, Hermes D and Staff N P 2020 The current state of electrocorticography-based brain–computer interfaces *Neurosurg. Focus* **49** E2

[101] Cardinale F, Casaceli G, Raneri F, Miller J and Lo Russo G 2016 Implantation of stereoelectroencephalography electrodes: a systematic review *J. Clin. Neurophysiol.* **33** 490–502

[102] Kirschstein T and Köhling R 2009 What is the source of the EEG? *Clin. EEG Neurosci.* **40** 146–9

[103] Schacter D L, Addis D R and Buckner R L 2007 Remembering the past to imagine the future: the prospective brain *Nat. Rev. Neurosci.* **8** 657–61

[104] Hassabis D, Kumaran D and Maguire E A 2007 Using imagination to understand the neural basis of episodic memory *J. Neurosci.* **27** 14365–74

[105] Szpunar K K, Watson J M and McDermott K B 2007 Neural substrates of envisioning the future *Proc. Natl Acad. Sci.* **104** 642–7

[106] Schacter D L, Addis D R, Hassabis D, Martin V C, Spreng R N and Szpunar K K 2012 The future of memory: remembering, imagining and the brain *Neuron* **76** 677–94

[107] Chadwick M J, Hassabis D, Weiskopf N and Maguire E A 2010 Decoding individual episodic memory traces in the human hippocampus *Curr. Biol.* **20** 544

[108] Bonnici H M, Chadwick M J, Lutti A, Hassabis D, Weiskopf N and Maguire E A 2012 Detecting representations of recent and remote autobiographical memories in vmPFC and hippocampus *J. Neurosci.* **32** 16982–91

[109] Rugg M D and Vilberg K L 2013 Brain networks underlying episodic memory retrieval *Curr. Opin. Neurobiol.* **23** 255–60

[110] Chen J, Leong Y C, Honey C J, Yong C H, Norman K A and Hasson U 2016 Shared memories reveal shared structure in neural activity across individuals *Nat. Neurosci.* **20** 115–25

[111] Baldassano C, Chen J, Zadbood A, Pillow J W, Hasson U and Norman K A 2017 Discovering event structure in continuous narrative perception and memory *Neuron* **95** 709–21.e5

[112] Mason R A and Just M A 2020 Neural representations of procedural knowledge *Psychol. Sci.* **31** 729–40

[113] Thirion B, Duchesnay E, Hubbard E, Dubois J, Poline J B, Lebihan D and Dehaene S 2006 Inverse retinotopy: inferring the visual content of images from brain activation patterns *NeuroImage* **33** 1104–16

[114] Kay K N, Naselaris T, Prenger R J and Gallant J L 2008 Identifying natural images from human brain activity *Nature* **452** 352–5

[115] Miyawaki Y, Uchida H, Yamashita O, Aki Sato M, Morito Y, Tanabe H C, Sadato N and Kamitani Y 2008 Visual image reconstruction from human brain activity using a combination of multiscale local image decoders *Neuron* **60** 915–29

[116] Naselaris T, Prenger R J, Kay K N, Oliver M and Gallant J L 2009 Bayesian reconstruction of natural images from human brain activity *Neuron* **63** 902–15

[117] Cichy R M, Heinzle J and Haynes J D 2012 Imagery and perception share cortical representations of content and location *Cereb. Cortex* **22** 372–80

[118] Pearson J 2019 The human imagination: the cognitive neuroscience of visual mental imagery *Nat. Rev. Neurosci.* **20** 624–34

[119] McNorgan C 2012 A meta-analytic review of multisensory imagery identifies the neural correlates of modality-specific and modality-general imagery *Front. Hum. Neurosci.* **6** 285

[120] Kosslyn S M, Thompson W L and Ganis G 2010 *The Case for Mental Imagery* (Oxford: Oxford University Press) pp 1–248

[121] Kosslyn S M, Ganis G and Thompson W L 2001 Neural foundations of imagery *Nat. Rev. Neurosci.* **2** 635–42
[122] Nanay B 2018 Multimodal mental imagery *Cortex* **105** 125–34
[123] Lacey S and Sathian K 2011 Multisensory object representation: insights from studies of vision and touch *Prog. Brain Res.* **191** 165–76
[124] Bruffaerts R, De Deyne S, Meersmans K, Liuzzi A G, Storms G and Vandenberghe R 2019 Redefining the resolution of semantic knowledge in the brain: advances made by the introduction of models of semantics in neuroimaging *Neurosci. Biobehav. Rev.* **103** 3–13
[125] Rosch E 1978 Principles of categorization *Readings in Cognitive Science: A Perspective From Psychology and Artificial Intelligence* (San Mateo, CA: Morgan Kaufmann) pp 312–22
[126] Binder J R, Conant L L, Humphries C J, Fernandino L, Simons S B, Aguilar M and Desai R H 2016 Toward a brain-based componential semantic representation *Cogn. Neuropsychol.* **33** 130–74
[127] Cree G S and McRae K 2003 Analyzing the factors underlying the structure and computation of the meaning of Chipmunk, Cherry, Chisel, Cheese and Cello (and many other such concrete nouns) *J. Exp. Psychol. Gen.* **132** 163–201
[128] Garrard P, Lambon Ralph M A, Hodges J R and Patterson K 2001 Prototypicality, distinctiveness and intercorrelation: analyses of the semantic attributes of living and nonliving concepts *Cogn. Neuropsychol.* **18** 125–74
[129] Ruts W, De Deyne S, Ameel E, Vanpaemel W, Verbeemen T and Storms G 2004 Dutch norm data for 13 semantic categories and 338 exemplars *Behav. Res. Methods Instrum. Comput.* **36** 506–15
[130] Palatucci M, Pomerleau D, Hinton G E and Mitchell T M 2009 Zero-shot learning with semantic output codes *Advances in Neural Information Processing Systems* vol 22
[131] Deerwester S, Dumais S T, Furnas G W, Landauer T K and Harshman R 1990 Indexing by latent semantic analysis *J. Am. Soc. Inf. Sci.* **41** 391–407
[132] Landauer T K and Dumais S T 1997 A solution to Plato's problem: the latent semantic analysis theory of acquisition, induction and representation of knowledge *Psychol. Rev.* **104** 211–40
[133] Mikolov T, Sutskever I, Chen K, Corrado G S and Dean J 2013 Distributed representations of words and phrases and their compositionality *Advances in Neural Information Processing Systems* vol 26
[134] Pennington J, Socher R and Manning C D 2014 GloVe: global vectors for word representation *EMNLP 2014–2014 Proc. 2014 Conf. on Empirical Methods in Natural Language Processing (EMNLP)* pp 1532–43
[135] Pereira F, Gershman S, Ritter S and Botvinick M 2016 A comparative evaluation of off-the-shelf distributed semantic representations for modelling behavioural data *Cogn. Neuropsychol.* **33** 175–90
[136] Miller G A and Charles W G 2007 Contextual correlates of semantic similarity *Lang. Cogn. Process.* **6** 1–28
[137] Clark S 2015 Vector space models of lexical meaning *The Handbook of Contemporary Semantic Theory* (New York: Wiley) pp 493–522
[138] Erk K 2012 Vector space models of word meaning and phrase meaning: a survey *Lang. Linguist. Compass* **6** 635–53
[139] Turney P D and Pantel P 2010 From frequency to meaning: vector space models of semantics *J. Artif. Intell. Res.* **37** 141–88
[140] Mikolov T, Chen K, Corrado G, and Dean J 2013 Efficient estimation of word representations in vector space (arXiv:1301.3781)
[141] Baroni M, Dinu G and Kruszewski G 2014 Don't count, predict! A systematic comparison of context-counting vs. context-predicting semantic vectors *52nd Annual Meeting of the Association for Computational Linguistics (ACL 2014)* vol 1 pp 238–47
[142] Hoffman P and Lambon Ralph M A 2018 From percept to concept in the ventral temporal lobes: graded hemispheric specialisation based on stimulus and task *Cortex* **101** 107–18
[143] Jung J Y, Williams S R, Sanaei Nezhad F and Lambon Ralph M A 2017 GABA concentrations in the anterior temporal lobe predict human semantic processing *Sci. Rep.* **7** 15748
[144] Müller-Gerking J, Pfurtscheller G and Flyvbjerg H 1999 Designing optimal spatial filters for single-trial EEG classification in a movement task *Clin. Neurophysiol.* **110** 787–98
[145] Blankertz B, Tomioka R, Lemm S, Kawanabe M and Müller K R 2008 Optimizing spatial filters for robust EEG single-trial analysis *IEEE Signal Process. Mag.* **25** 41–56
[146] Anzai Y 1992 *Pattern Recognition & Machine Learning* (Amsterdam: Elsevier)
[147] Alpaydin E 2004 *Introduction to Machine Learning* (Cambridge, MA: MIT Press)
[148] Lecun Y, Bengio Y and Hinton G 2015 Deep learning *Nature* **521** 436–44
[149] Shamsi F *et al* 2019 Deep learning for electroencephalogram (EEG) classification tasks: a review *J. Neural Eng.* **16** 031001
[150] McFarland D J, Sarnacki W A and Wolpaw J R 2003 Brain–computer interface (BCI) operation: optimizing information transfer rates *Biol. Psychol.* **63** 237–51
[151] Wolpaw J R *et al* 2000 Brain-computer interface technology: a review of the first international meeting *IEEE Trans. Rehabil. Eng.* **8** 164–73
[152] Shannon C 1948 A Mathematical theory of communication *Bell Syst. Tech. J.* **27** 379–423
[153] Billinger M, Daly I, Kaiser V, Jin J, Allison B, Müller-Putz G and Brunner C 2012 Is it significant? Guidelines for reporting BCI performance *Towards Practical Brain-Computer Interfaces* ed B Z Allison, S Dunne, R Leeb, J D R Milan and A Nijholt (Berlin: Springer) pp 333–54
[154] Haxby J V, Guntupalli J S, Connolly A C, Halchenko Y O, Conroy B R, Gobbini M I, Hanke M and Ramadge P J 2011 A common, high-dimensional model of the representational space in human ventral temporal cortex *Neuron* **72** 404–16
[155] Friston K J K J, Ashburner J, Kiebel S, Nichols T and Penny W D 2007 *Statistical Parametric Mapping: The Analysis of Functional Brain Images* (Amsterdam: Elsevier)
[156] Kriegeskorte N 2008 Representational similarity analysis—connecting the branches of systems neuroscience *Front. Syst. Neurosci.* **2** 1
[157] Dubossarsky H, De Deyne S and Hills T T 2017 Quantifying the structure of free association networks across the life span *Dev. Psychol.* **53** 1560–70
[158] Yang Y, Wang J, Bailer C, Cherkassky V and Just M A 2017 Commonality of neural representations of sentences across languages: predicting brain activation during Portuguese sentence comprehension using an English-based model of brain function *NeuroImage* **146** 658–66
[159] Zinszer B D, Anderson A and Raizada R D S 2016 Chinese and English speakers' neural representations of word meaning offer a different picture of cross-language semantics than corpus and behavioral measures *Cognit. Sci.*
[160] Raizada R D S and Connolly A C 2012 What makes different people's representations alike: neural similarity space solves the problem of across-subject fMRI decoding *J. Cogn. Neurosci.* **24** 868–77
[161] Mur M, Bandettini P A and Kriegeskorte N 2009 Revealing representational content with pattern-information fMRI—an introductory guide *Soc. Cogn. Affect. Neurosci.* **4** 101–9
[162] Tu K, Cooper D G and Siegelmann H T 2009 Memory reconsolidation for natural language processing *Cogn. Neurodyn.* **3** 365–72

[163] Güçlütürk Y, Güçlü U, van Gerven M and van Lier R 2018 Representations of naturalistic stimulus complexity in early and associative visual and auditory cortices *Sci. Rep.* **8** 3439
[164] Rosch E, Mervis C B, Gray W D, Johnson D M and Boyes-Braem P 1976 Basic objects in natural categories *Cogn. Psychol.* **8** 382–439
[165] Bray S, Chang C and Hoeft F 2009 Applications of multivariate pattern classification analyses in developmental neuroimaging of healthy and clinical populations *Front. Hum. Neurosci.* **3** 32
[166] Mórocz I A, Janoos F, van Gelderen P, Manor D, Karni A, Breznitz Z, von Aster M, Kushnir T and Shalev R 2012 Time-resolved and spatio-temporal analysis of complex cognitive processes and their role in disorders like developmental dyscalculia *Int. J. Imaging Syst. Technol.* **22** 81–96
[167] Pasley B N and Knight R T 2013 Decoding speech for understanding and treating aphasia *Prog. Brain Res.* **207** 435–56
[168] Janoos F, Brown G, Mórocz I A and Wells W M 2013 State-space analysis of working memory in schizophrenia: an FBIRN study *Psychometrika* **78** 279–307
[169] Sternberg S 1966 High-speed scanning in human memory *Science* **153** 652–4
[170] Just M A, Cherkassky V L, Buchweitz A, Keller T A and Mitchell T M 2014 Identifying autism from neural representations of social interactions: neurocognitive markers of autism *PLoS One* **9** e113879
[171] Heinsfeld A S, Franco A R, Craddock R C, Buchweitz A and Meneguzzi F 2018 Identification of autism spectrum disorder using deep learning and the ABIDE dataset *NeuroImage Clin.* **17** 16–23
[172] Anderson A J and Lin F 2019 How pattern information analyses of semantic brain activity elicited in language comprehension could contribute to the early identification of Alzheimer's Disease *NeuroImage Clin.* **22** 101788
[173] Pakhomov S V, Hemmy L S and Lim K O 2012 Automated semantic indices related to cognitive function and rate of cognitive decline *Neuropsychologia* **50** 2165–75
[174] Just M A, Pan L, Cherkassky V L, McMakin D L, Cha C, Nock M K and Brent D 2017 Machine learning of neural representations of suicide and emotion concepts identifies suicidal youth *Nat. Hum. Behav.* **1** 911–9
[175] Wolpaw J R 2007 Brain-computer interfaces as new brain output pathways *J. Physiol.* **579** 613–9
[176] Wolpaw J R, Birbaumer N, McFarland D J, Pfurtscheller G and Vaughan T M 2002 Brain-computer interfaces for communication and control *Clin. Neurophysiol.* **113** 767–91
[177] Hill N J, Ricci E, Haider S, McCane L M, Heckman S, Wolpaw J R and Vaughan T M 2014 A practical, intuitive brain–computer interface for communicating 'yes' or 'no' by listening *J. Neural Eng.* **11** 035003
[178] Kleih S C, Herweg A, Kaufmann T, Staiger-Sälzer P, Gerstner N and Kübler A 2015 The WIN-speller: a new intuitive auditory brain-computer interface spelling application *Front. Neurosci.* **9** 346
[179] Albilali E, Aboalsamh H and Al-Wabil A 2013 Comparing brain-computer interaction and eye tracking as input modalities: an exploratory study *2013 Int. Conf. on Current Trends in Information Technology (CTIT)* (IEEE) pp 232–6
[180] Suefusa K and Tanaka T 2017 A comparison study of visually stimulated brain–computer and eye-tracking interfaces *J. Neural Eng.* **14** 036009
[181] Zhou S, Jin J, Daly I, Wang X and Cichocki A 2016 Optimizing the face paradigm of BCI system by modified mismatch negative paradigm *Front. Neurosci.* **10** 444
[182] Volosyak I and Rhein-Waal H 2016 *EEG-Based Brain-Computer Interfaces for Healthcare Applications* (Shaker Verlag: Herzogenrath) (http://uir.ulster.ac.uk/33371/)
[183] Tauroza S and Allison D 1990 Speech rates in British English *Appl. Linguist.* **11** 90–105
[184] Bochkarev V V, Shevlyakova A V and Solovyev V D 2012 Average word length dynamics as indicator of cultural changes in society (arXiv:1208.6109)
[185] Pasqualotto E, Matuz T, Federici S, Ruf C A, Bartl M, Olivetti Belardinelli M, Birbaumer N and Halder S 2015 Usability and workload of access technology for people with severe motor impairment *Neurorehabil. Neural Repair* **29** 950–7
[186] Hwang H-J, Lim J-H, Jung Y-J, Choi H, Lee S W and Im C-H 2012 Development of an SSVEP-based BCI spelling system adopting a QWERTY-style LED keyboard *J. Neurosci. Methods* **208** 59–65
[187] Kapeller C, Kamada K, Ogawa H, Prueckl R, Scharinger J and Guger C 2014 An electrocorticographic BCI using code-based VEP for control in video applications: a single-subject study *Front. Syst. Neurosci.* **8** 139
[188] Wairagkar M, Daly I, Hayashi Y and Nasuto S 2014 Novel single trial movement classification based on temporal dynamics of EEG *6th Int. Brain-Computer Interface Conf. Graz, Austria* (http://centaur.reading.ac.uk/37412/1/Graz conference 2014-Final version.pdf)
[189] Jin J, Daly I, Zhang Y, Wang X and Cichocki A 2014 An optimized ERP brain-computer interface based on facial expression changes *J. Neural Eng.* **11** 036004
[190] Kaufmann T, Schulz S M, Grünzinger C and Kübler A 2011 Flashing characters with famous faces improves ERP-based brain-computer interface performance *J. Neural Eng.* **8** 056016
[191] Chen L, Jin J, Daly I, Zhang Y, Wang X and Cichocki A 2016 Exploring combinations of different color and facial expression stimuli for gaze-independent BCIs *Front. Comput. Neurosci.* **10** 5
[192] Huang M, Daly I, Jin J, Zhang Y, Wang X and Cichocki A 2016 An exploration of spatial auditory BCI paradigms with different sounds: music notes versus beeps *Cogn. Neurodyn.* **10** 201–9
[193] Pfurtscheller G, Solis-Escalante T, Ortner R, Linortner P and Müller-Putz G R 2010 Self-paced operation of an SSVEP-Based orthosis with and without an imagery-based 'brain switch': a feasibility study towards a hybrid BCI *IEEE Trans. Neural Syst. Rehabil. Eng.* **18** 409–14
[194] Wang M, Daly I, Allison B Z, Jin J, Zhang Y, Chen L and Wang X 2014 A new hybrid BCI paradigm based on P300 and SSVEP *J. Neurosci. Methods* **244** 16–25
[195] Rupp K, Roos M, Milsap G, Caceres C, Ratto C, Chevillet M, Crone N E and Wolmetz M 2017 Semantic attributes are encoded in human electrocorticographic signals during visual object recognition *NeuroImage* **148** 318–29
[196] McCartney B, Martinez-del Rincon J, Devereux B and Murphy B 2019 A zero-shot learning approach to the development of brain-computer interfaces for image retrieval *PLoS One* **14** e0214342
[197] Geuze J, Farquhar J, Desain P, van Gerven M and Horki P 2014 Towards a communication brain computer interface based on semantic relations *PLoS One* **9** e87511
[198] Wenzel M A, Bogojeski M and Blankertz B 2017 Real-time inference of word relevance from electroencephalogram and eye gaze *J. Neural Eng.* **14** 056007
[199] Andersen R A, Hwang E J and Mulliken G H 2010 Cognitive neural prosthetics *Annu. Rev. Psychol.* **61** 169–90
[200] Nagals-Coune L, Kurban D, Reuter N, Benitez A, Gosse L, Riecke L, Goebel R and Sorger B 2017 Yes or No?—binary brain-based communication utilizing motor imagery and fNIRS *7th Graz Brain-Computer Interface Conf. 2017* pp 355–60
[201] Sorger B, Dahmen B, Reithler J, Gosseries O, Maudoux A, Laureys S and Goebel R 2009 Another kind of 'BOLD Response': answering multiple-choice questions via online decoded single-trial brain signals *Prog. Brain Res.* **177** 275–92

[202] Johansen J D and Larsen S E 2002 *Signs in Use: An Introduction to Semiotics* (Oxfordshire: Routledge) p 246
[203] Timofeeva M 2016 Semiotic training for brain-computer interfaces *2016 Federated Conf. Computer Science and Information Systems (FedCSIS)* (IEEE) pp 921–5
[204] Ariely D and Berns G S 2010 Neuromarketing: the hope and hype of neuroimaging in business *Nat. Rev. Neurosci.* **11** 284–92
[205] Mecacci G and Haselager P 2019 Identifying criteria for the evaluation of the implications of brain reading for mental privacy *Sci. Eng. Ethics* **25** 443–61