Mapping the Semantic Structure of Cognitive Neuroscience

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Abstract

■ Cognitive neuroscience, as a discipline, links the biological systems studied by neuroscience to the processing constructs studied by psychology. By mapping these relations throughout the literature of cognitive neuroscience, we visualize the semantic structure of the discipline and point to directions for future research that will advance its integrative goal. For this purpose, network text analyses were applied to an exhaustive corpus of abstracts collected from five major journals over a 30-month period, including every study that used fMRI to investigate psychological processes. From this, we generate network maps that illustrate the relationships among psychological and anatomical terms, along with centrality statistics that guide inferences about network structure. Three terms—*prefrontal cortex*, *amygdala*, and *anterior cingulate cortex*—dominate the network structure with their high frequency in the literature and the density of their connections with other neuroanatomical terms. From network statistics, we identify terms that are understudied compared with their importance in the network (e.g., *insula* and *thalamus*), are underspecified in the language of the discipline (e.g., terms associated with executive function), or are imperfectly integrated with other concepts (e.g., subdisciplines like decision neuroscience that are disconnected from the main network). Taking these results as the basis for prescriptive recommendations, we conclude that semantic analyses provide useful guidance for cognitive neuroscience as a discipline, both by illustrating systematic biases in the conduct and presentation of research and by identifying directions that may be most productive for future research. ■

INTRODUCTION

In its relatively brief history, cognitive neuroscience has emerged from an amorphous integration of systems neuroscience, computational neuroscience, and cognitive psychology into a mature enterprise with hundreds of newly published studies every month. Results obtained using the core techniques of cognitive neuroscience—notably fMRI—now shape our understanding not only of brain function but also of associated psychological and computational concepts. Each new experiment establishes or strengthens links between the neural structures studied by neuroscience and the cognitive and behavioral constructs revealed by psychology. Over time, studies combine into a web of accumulated knowledge (i.e., a semantic structure) that links brain function to cognition.

Mapping the semantic structure of cognitive neuroscience would have important consequences. To the extent that the existing research is a true reflection of the relationship between brain and cognition, syntheses can illustrate commonalities across many studies. Recent years have seen an increase in the use of formal methods for unbiased synthesis of the literature (Levallois, Clithero, Wouters, Smidts, & Huettel, 2012; Evans & Foster, 2011; Shiffrin & Borner, 2004). Such methods range from those that combine patterns of activation across studies to identify associations between mental processes and locations in the brain (e.g., activation likelihood estimation; Yarkoni, Poldrack, Nichols, Van Essen, & Wager, 2011; Yarkoni, Poldrack, Van Essen, & Wager, 2010; Nielsen, 2009; Van Essen, 2009) to those that employ statistical analyses of many studies using bibliometrics and co-citation analyses (Behrens, Fox, Laird, & Smith, 2013; Viedma-del-Jesus, Perakakis, Munoz, Lopez-Herrera, & Vila, 2011; Bruer, 2004, 2010; Burright, Hahn, & Antonisse, 2005; Robins, Gosling, & Craik, 1999). Linking these different levels are new forms of ontological meta-analyses that characterize the conceptual framework among findings in cognitive neuroscience, so that new results can be integrated into a semantic infrastructure (Poldrack et al., 2011; Poldrack, 2010).

An alternative approach to meta-analysis—semantic network analysis—examines the textual properties of a corpus (e.g., published articles within a scientific discipline) to examine the interrelations of its constituent elements. These techniques combine information about the co-occurrence of individual terms to produce maps of their interrelations and therefore provide an aggregate means by which to visually and statistically map concepts that appear in the larger literature (Diesner & Carley, 2005; Mehl, 2005; Popping, 2000; Carley, 1997). This approach has both practical and analytic advantages. It leverages the accessibility of digital articles, avoiding the difficulty

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of compiling primary data from a large and exponentially growing literature. Moreover, it can provide insight into how knowledge is organized in the minds of authors and is expressed in the discourse of their published findings. The meaningful elements of a discipline (e.g., key terms) can be combined into a semantic structure that reflects the superordinate conceptual level through which results are interpreted and hypotheses are conceived.

The semantic structure of cognitive neuroscience need not be isomorphic with the natural phenomena it investigates, because of biases inherent in common research practices. A first and well-recognized source of bias comes from increasing specialization by researchers. Research on a given topic may proceed rapidly within one specialty, but incrementally in another—and the boundaries between different specialties may be more or less permeable. Second, imprecision in terminology may lead to both unnecessary distinctions and unwanted conflations. What one study describes as working memory, another may posit as cognitive control. Even the labeling of brain regions can be subject to terminological biases; witness, for example, the variation in what parts of the medial frontal lobe are subsumed within anterior cingulate cortex. Third, once a brain structure is linked to some function, that link can shape the direction of future research, both because of the tendency to favor information consistent with preexisting beliefs (i.e., confirmation bias) and reification of concepts by applying old labels to new findings. Collectively, these biases could lead to large-scale gaps in the literature. Such understudied topics or brain structures would not be evident within traditional research syntheses—but they may be uncovered by examining anomalies in the field's semantic structure, as has been done for other fields like sociology (Moody & Light, 2006).

Network analytic techniques can provide an important tool for identifying such biases and anomalies and for evaluating their impact. If the semantic structure obtained from the text perfectly tracks existing relationships, then the network is expected to have certain properties. Centrality measures, for example, provide statistical assessments of a term's placement within the larger network (e.g., terms with high betweenness centrality often lie along the shortest paths between other terms in the network), and it would be expected that higher centrality would be positively correlated with term frequency, because frequent terms are more likely to have systematic connections with other terms. Some terms, however, may be outliers—such that they are more or less central than their frequency would predict. Identification of these terms can reveal inefficiencies within the literature (e.g., confirmation biases, over- or underemphasis on research on a topic) and provide an important means to scrutinize the knowledge structure contained within a body of text.

Here, we apply techniques of network analysis to a comprehensive corpus from the literature. This method is particularly suitable for cognitive neuroscience, given the field's goal of building links between two distinct semantic categories (i.e., brain structures and cognitive functions). Moreover, each of these categories has meaningful internal organization: Brain structures are frequently organized into systems that describe processing pathways, whereas cognitive functions are grouped into higher-level concepts that label their shared computations. By mapping the relationships within and across the anatomical and conceptual components of cognitive neuroscience, we not only characterize the current structure of the discipline but also identify anomalies that indicate important directions for future research. Like a geographic atlas, our network maps describe both well-trodden and familiar research paths as well as islands of uncharted territory.

METHODS

Assembly of the Corpus

We sought a representative sample of articles in the field of cognitive neuroscience, which we defined operationally through a selection of contemporary papers with the common aim of relating brain anatomy with behavioral function. For this purpose, we collected every article published between January 1, 2008 and June 30, 2010 in five leading journals: *Nature Neuroscience*, *Neuron*, *Journal of Cognitive Neuroscience*, *Neuroimage*, and *Journal of Neuroscience*. This raw corpus contained 7675 studies, which were individually assessed for adherence to the following conditions for inclusion:

A. Use of fMRI for primary data collection.
B. Stated goals of understanding links between the human brain and some psychological function.
C. A report of empirical data collected for the current article.

The rationale for each criterion is discussed below. After discarding articles that did not meet these standards, the corpus was narrowed to 1127 studies. The text of the corpus consisted of the title and abstract of each accepted article.

Criterion A

By restricting our analysis to studies that employed a common neuroimaging method, we minimized differences in terminology and rhetoric. fMRI was selected because of its popularity: It was the most widely used human neuroimaging technique in the unfiltered pool of studies (employed by 1359 before applying the second criterion). In comparison, all other human imaging techniques combined were less than half as frequent: EEG (346), PET (120), and TMS (109). In the case that a study made use of more than one technique, it was accepted only if its empirical conclusions depended directly on fMRI data. Hence, whereas synchronous EEG-fMRI studies were included, fMRI-guided TMS studies were not. We note that fMRI is used for investigation of practically all concepts in cognitive neuroscience, making its studies a good proxy for the larger literature.

Criterion B

The second criterion ensured that our studies were clearly within cognitive neuroscience, as commonly defined. We excluded methodological studies, such as those that sought to advance fMRI technology, to develop tasks for fMRI experiments, or to characterize the fMRI hemodynamic response. Studies that used fMRI for atlas generation were likewise discarded, as they did not aim to correlate brain anatomy with psychological function. Animal studies were not included because of the incongruences between humans and animals in brain organization and behavioral repertoire.

Criterion C

Finally, we limited the corpus to empirical articles presenting new fMRI data. This restriction minimized bias from articles reinterpreting or reanalyzing former results. Meta-analyses and review articles were thus omitted, as were studies that applied novel statistical or computational models to previously published data.

Term Classification and Text Preprocessing

Separate semantic categories were created for anatomy and concept terms. Anatomy terms referred to either a brain structure (e.g., *hippocampus*) or a functionally defined region (e.g., *fusiform face area*). Concept terms were either a domain of cognitive neuroscience (e.g., *memory*), a process within a domain (e.g., *working memory*), or a property of the experimental stimuli (e.g., *face* or *risk*).

A list of all unique words (15,127) in the corpus of abstracts was generated and sorted by frequency, and the 100 most frequent anatomy and concept terms were manually identified (Appendix 1 and 2). The terms used to generate the networks were the most frequent word forms to appear in the text after preprocessing. The final judgment of term appropriateness for the two lists was made by two expert raters (authors LGA and SAH) who evaluated every candidate term.

The corpus was preprocessed in Automap (Carley, 2010a) to normalize for grammatical variants of anatomy and concept terms. Because standard thesauri include neither neuroanatomical terms nor the jargon of cognitive neuroscience, we authored custom thesauri. First, a bigram thesaurus was created to collapse word pairs to single words by replacing spaces with underscores. This involved generating a frequency-sorted semantic list, identifying anatomy or concept word pairs that appeared at a higher frequency than the 100th most frequent anatomy or concept term and creating a list of the word pairs and the consolidated terms. The process iterated for longer phrases, for example, *primary somatosensory* was converted to *primary_somatosensory* and then *primary_somatosensory cortex* became *primary_somatosensory_cortex*. Adjustments were made to the top 100 lists of anatomy and concept terms after the bigram thesaurus was applied to accommodate phrases that appeared at higher frequencies than the initially identified one-word terms. Second, a generalization thesaurus was created to normalize for plurals, acronyms, and hyphenated compounds. All instances of plurals were normalized, but the remaining entries in the bigram and generalization thesauri were created only for variants that appeared at a higher frequency than the 100th anatomy or concept term. The lowest frequency threshold was imposed to limit manual searching for variants in the frequency list. Finally, titles were assigned to nodes on the visualization after capitalizing terms and separating consolidated phrases into single words.

Network Generation

Automap software was used to generate a meta-network comprised of links within and between anatomy and concept node classes. The Conceptual, Anatomical, and Functional Networks are substructures within this meta-network. A link was identified as the co-occurrence of two terms within a moving window of six adjacent words that appeared in the same sentence. The selection of these parameters was made based on previous text analytic studies (Diesner & Carley, 2004) and supported by a series of systematic analyses. To check that the network structure is robust against window size manipulations, additional networks were generated across a range of the window size parameter. This analysis revealed that the mean betweenness centrality was relatively stable at widow sizes greater than four words in length. Thus, a network derived from a moving window of six words possesses a structure that is maintained across small manipulations of the window size parameter.

Links were directed from the first to the second term, as read from left to right across the text within the window. Link weights were calculated from the sum of term co-occurrences throughout the corpus and were used to construct the three networks: Conceptual (concepts to concepts), Anatomical (anatomy to anatomy), and Functional (anatomy to concepts and concepts to anatomy). To confirm that the structure of these networks is dependent on the relative position of words in the text, additional networks were generated from a text-scrambled version of the corpus. Networks generated from these scrambled texts were organized with central positions occupied by the most frequent terms, as expected from a frequency-weighted probability of random co-occurrences between terms. Likewise, the discrete nodal connections in these scrambled networks varied from those in the original networks and did not provide any meaningful structure for concepts or anatomy, thereby providing confirmation that the networks under consideration are in fact dependent on the word arrangements in the original corpus.

Network Visualization

The networks were visualized using Organization Risk Analyzer software (Carley, 2010b). Nodes were sized in proportion to frequency and colored according to membership in the anatomy or concept node class. The relative thickness of lines was scaled to link weight, and arrowheads were added to indicate link directionality. We selected the threshold for link weighting to restrict the network visualizations to the 50 most strongly connected nodes. In the case of the Functional Network, because there were not 50 nodes at the same weighting level, 54 nodes were retained. To ensure that the visualizations contained structures insensitive to thresholding, we assessed the number of links visualized at every threshold level. Whereas the weakest links were eliminated rapidly with increasing threshold, the rate of decrease in link number neared zero at and above the thresholds we selected. This result affirmed both that unstable structures were eliminated from the visualizations and that the structures we visualized were upheld across a wide range of thresholds levels.

To further aid in visualization, a hyperbolic magnification was applied to expand the center of each network. The positions of some nodes were manually adjusted within a small radius to minimize overlapping of links and node titles. Islands of more than one node that exceeded threshold and were isolated from the main network were repositioned to improve the visualization layout, while still maintaining the local network structure of the island.

Network Measures

Quantitative analysis of the networks was conducted through Organization Risk Analyzer software. Measures were computed for all nodes, including nodes below the threshold for visualization. On the level of the entire network, density was calculated from the ratio of the number of links to the maximum possible number of links. Node level measures of centrality were calculated for total degree, eigenvector, and betweenness (Carley & Reminga, 2004; Freeman, 1977).

Total degree is a simple measure of the amount of information that passes through a node. It was computed as the number of other terms to which each term was directly linked. Nodes with high degree centrality are characterized by a high informational load because of the density of their connections, yet because degree is a local measure, they do not necessarily carry the relational information that determines the global structure of a network. For this reason, we calculate two more sophisticated centrality metrics: eigenvector centrality and betweenness centrality.

Eigenvector centrality is a measure of a node's connectedness—specifically, of the extent to which a node is linked to other highly linked nodes. The eigenvector centrality of a node is proportional to the sum of the eigenvectors of its first-degree neighbors. In some network structures, terms with high eigenvector centrality cluster in a hub at the center of the network, surrounded by groups of terms at the periphery that are more strongly intraconnected than they are connected to rest of the network. Identifying terms that form central hubs is important for understanding how distinct domains are related at the core of the discipline. Although we use eigenvector centrality to quantify the positive organization of terms that we observe in the network visualizations, we require another measure to identify anomalies of the network structure.

Betweenness centrality is a measure of the bridging role a node plays between regions throughout the network, computed as the proportion of times a term fell on the shortest path between pairs of other terms. Of particular interest will be nodes that have high betweenness centrality despite being of low frequency; we highlight those nodes as targets for research that seeks to strengthen relationships between subfields.

We found that total degree centrality was correlated with frequency (R^2 = .89 for the Conceptual Network, R^2 = .75 for the Anatomical Network; R^2 = .67 and .89 for the concept and anatomy nodes of the Functional Network, respectively). Because of this correlation and to ease interpretability, frequency was used as a proxy for degree centrality in plots of centrality measures. Betweenness centrality was plotted against frequency to identify nodes that are more important to the network than predicted by their popularity in the literature.

The Functional Network consists of two component (unidirectional) two-mode networks: the anatomy-by-concept and the concept-by-anatomy. For the visualization, these networks share a single projection and the direction of the arrow indicates the two-mode component network for a given link. Quantitative analysis of each two-mode network was conducted independently (i.e., taking into account directionality in the text), and the visualization shows the combination of the two analyses.

Second-level Positional Analyses

The Conceptual, Anatomical, and Functional Networks were projected to show shared links between nodes. Unlike traditional cluster analyses that pair nodes in a hierarchical fashion beginning with the strongest first-degree connections, our approach computes a weighted measure of how similar two nodes are in their connections throughout the network. The resulting second-order positional networks convey information about global similarities in connectivity within each link. Strong connections between nodes in such networks can indicate terms that perform similar roles in the literature, as in the case where they operate as structural synonyms that can be interchangeable across contexts.

First, adjacency matrices of link weights between concept-by-concept, anatomy-by-anatomy, and concept-by-anatomy nodes were extracted from the networks. Structural similarity was then computed in MATLAB by calculating the correlation coefficient between each row. The structural similarity measures were used to create second-order networks that were visualized in UCINET (Borgatti, Everett, & Freeman, 2002) and thresholded by link weight to show the top 20 most strongly connected nodes. Although thresholding resulted in a higher proportion of nodes belonging to dyads or triads than larger multinode structures compared with unthresholded projections, the elimination of weak higher-order structures is suited to our aim of identifying nodes with the most closely correlated connectivity patterns as structural synonyms.

RESULTS

Applying network analytic techniques led to the construction of three networks: a Conceptual Network, reflecting connections between concept terms (e.g., *memory* to *representation*); an Anatomical Network, reflecting connections between brain structures (e.g., *prefrontal cortex* to *hippocampus*); and a Functional Network, reflecting connections between concept terms and brain structures (e.g., *amygdala* to *emotion*). These three networks provide distinct insights into how the field of cognitive neuroscience semantically links cognitive concepts, brain structures, and their functional relations, respectively.

Conceptual Structure

Examination of the Conceptual Network (Figure 1A) revealed a central hub of core concepts that, with their connections, group into three divisions: perception/attention, representation/memory, and cognition/control. As a result of their positions near highly linked nodes, the terms that fall along the central hub each rank high in eigenvector centrality (*vision* is 2nd, *attention* is 4th, *object* is 6th, *control* is 7th, *representation* is 9th, and *motor* is 18th). Of these, most counterintuitive is that *memory*—the second-most-common conceptual term in the literature and ranked first in eigenvector centrality—does not fall along the central hub but instead lies within a strongly interconnected cluster of terms that describe both semantic properties (i.e., *representation*, *category*) and the storage and manipulation of those properties (i.e., *recognition*).

Notable, as well, is the presence of groups of terms that are disconnected from the main network. The largest of

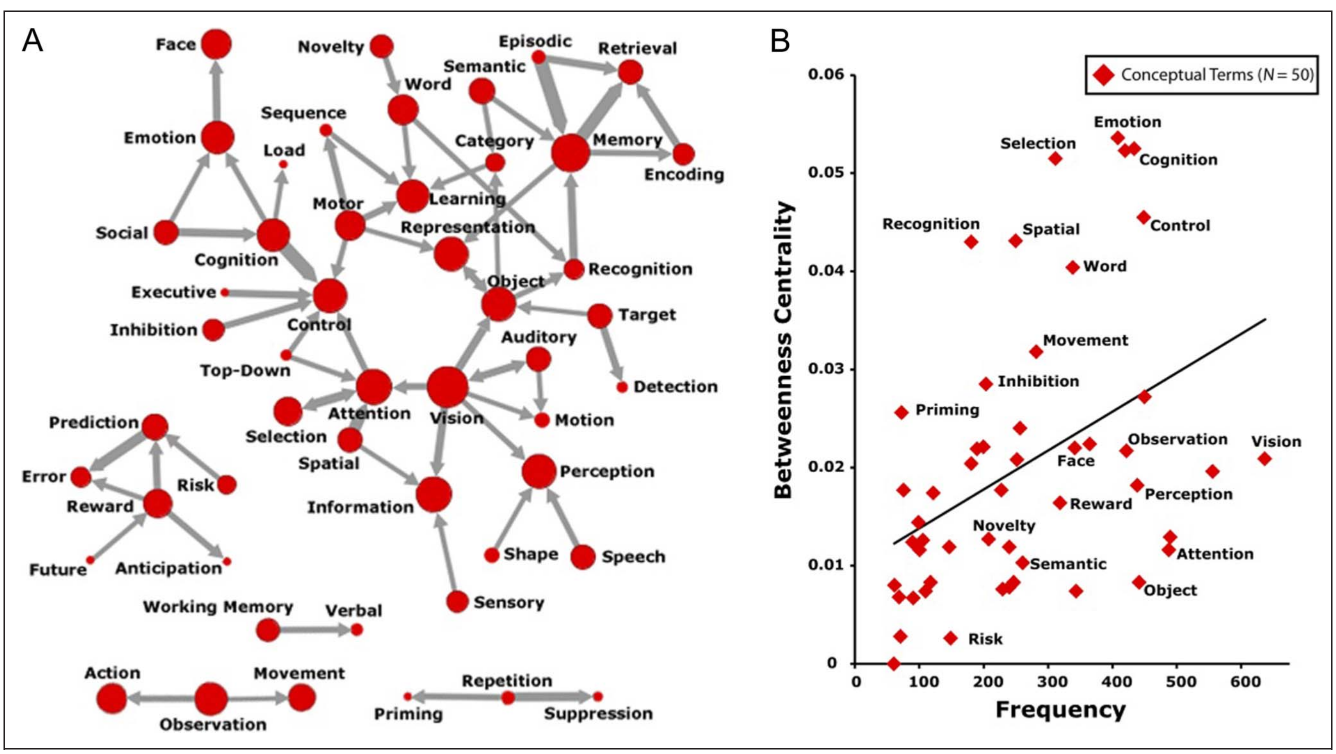


Figure 1. Conceptual Network visualization and measures. (A) Network visualization representing the psychological underpinnings of the cognitive neuroscience field (density = 0.28). The top 50 strongest linked terms as determined by a link weighting threshold (>51). Term frequency is indicated by the diameter of each node. Link weight is indicated by line width and directionality (in the text) is shown by the arrows. (B) Plot of betweenness centrality versus frequency for the 50 concept terms visualized.

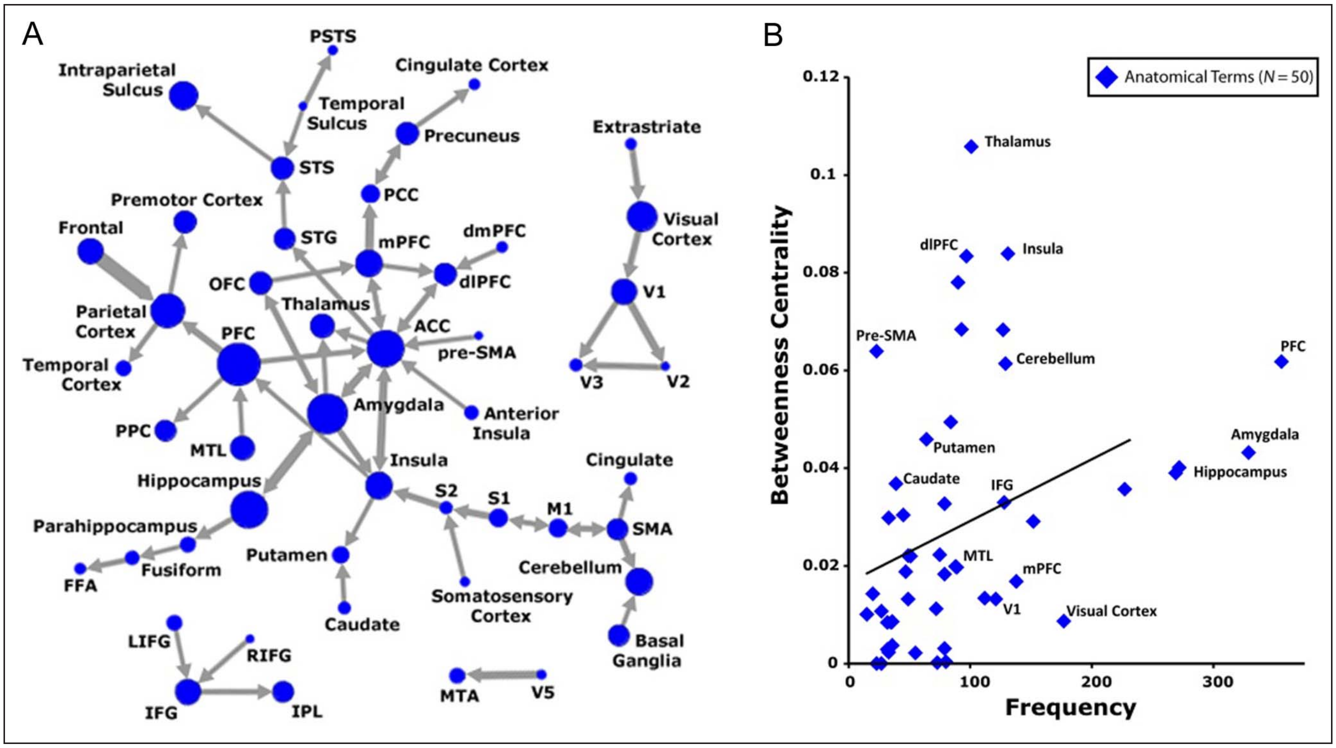


Figure 2. Anatomical Network visualization and measures. (A) Network visualization representing the anatomical underpinnings of the cognitive neuroscience field (density = 0.13). The top 50 strongest linked terms as determined by a link weighting threshold (>21). (B) Plot of betweenness centrality versus frequency for the 50 anatomical terms visualized.

these, shown at bottom left, contains key concepts related to decision-making, such as *risk* and *reward*. A natural interpretation is that research investigating these concepts—often considered within the emerging discipline of neuroeconomics (Smith & Huettel, 2010)—has proceeded as an autonomous discipline with its own well-developed internal structure of concepts. The distribution of intra-island connections is skewed toward higher link weights than the distribution of interisland connections, so the island is more strongly interconnected than it is connected to the rest of the network. We note that this disconnection is not a function of an arbitrary display threshold: At every possible threshold, the connections within the neuroeconomics cluster are substantially stronger than the connections from that group to the main body of the network.

For each term in the conceptual network, we examined the relationship between two measures of network centrality (Figure 1B). As might be expected, more common terms (frequency; x axis) tend to serve more of a linking role in the network (betweenness; y axis). Yet, these statistical measures reveal that terms tend to cluster along two sequences, as evident from the bimodal nature of the graph. At bottom right lie the canonical domains of cognitive neuroscience (e.g., *vision*, *memory*, *attention*); despite their frequency, these terms do not support many links between other concepts in the discipline (i.e., they have lower-than-predicted betweenness). At the top of the plot reside processes that span those domains (e.g., *emotion*, *control*, *selection*); although not as frequent, these terms have high betweenness and serve a bridging role within the network.

Anatomical Structure

The network map of anatomical structures (Figure 2A), unlike the conceptual map just described, neither exhibited a central hub nor self-organized into categorical groupings. Instead, its structure was dominated by three terms, each highly frequent and each densely interconnected with other nodes: *prefrontal cortex*, *amygdala*, and *anterior cingulate*. From these and other common terms, long branches linked successions of terms within processing pathways (e.g., a sensorimotor branch linking cortical and subcortical regions, beginning at *S1/S2* and ending with the *basal ganglia*). Three groups of terms were unconnected to the main network: two of these described visual regions and one characterized subregions in prefrontal and parietal cortex. In the aggregate, this network was markedly less dense (0.13) and had proportionally fewer interconnections than the conceptual network (0.28). Moreover, the connections only imperfectly track known anatomical relations.

Analysis of network centrality statistics (Figure 2B) revealed that several anatomical regions occupy a disproportionally central place in the network compared with their frequency. The *thalamus* and *insula* had the highest and second-highest betweenness centrality of any structure, despite only being the 15th and 9th most common terms, respectively. These outliers tend to co-occur in the literature with a diverse array of other regions, potentially reflecting their contributions to many of the processes studied by cognitive neuroscience. Furthermore, their network statistics (i.e., high betweenness relative to frequency) means that additional studies of their function would have the greatest effects on the overall character of the network. Accordingly, we consider them particularly important targets for future research.

Functional Structure

We constructed a network containing bidirectional links between concepts and anatomy; this two-mode Functional Network (Figure 3A) provides the most direct example of the semantic structure of cognitive neuroscience. Although this network contains similar numbers of terms in each category, its structure is driven by anatomical terms. The network statistics (Figure 3B) revealed that anatomical terms have higher betweenness centrality than conceptual terms, although the latter are more frequent. That is, information about anatomy contributes more than information about concepts in defining relationships within the literature. Of the anatomical terms, four are the most central in this network: *prefrontal cortex*, *amygdala*, *parietal cortex*, and *hippocampus*.

Conversely, many of the high-frequency conceptual terms are on the margins of the network. Some are pendants with only one above-threshold connection, for example, *object*, *emotion*, *information*, *observation*. Others are part of dyads or triads that are disconnected from the main network at this threshold, for example, *V1* and *representation*. Such results may seem paradoxical because, as noted previously, some of these terms were highly central within the map of concepts themselves. Yet, this functional map provides different information, in that it considers only links across categories. Thus, terms that may be very central in the conceptual map (i.e., the bridging processes described earlier) may be on the periphery of the current functional map if they are primarily linked to one or a small set of brain regions (e.g., *emotion* to the *amygdala*)—whether because of functional specificity or because new research tends to reify the results of older studies.

Structural Synonymy

For all three analyses described above, we created second-order positional networks based on the structural

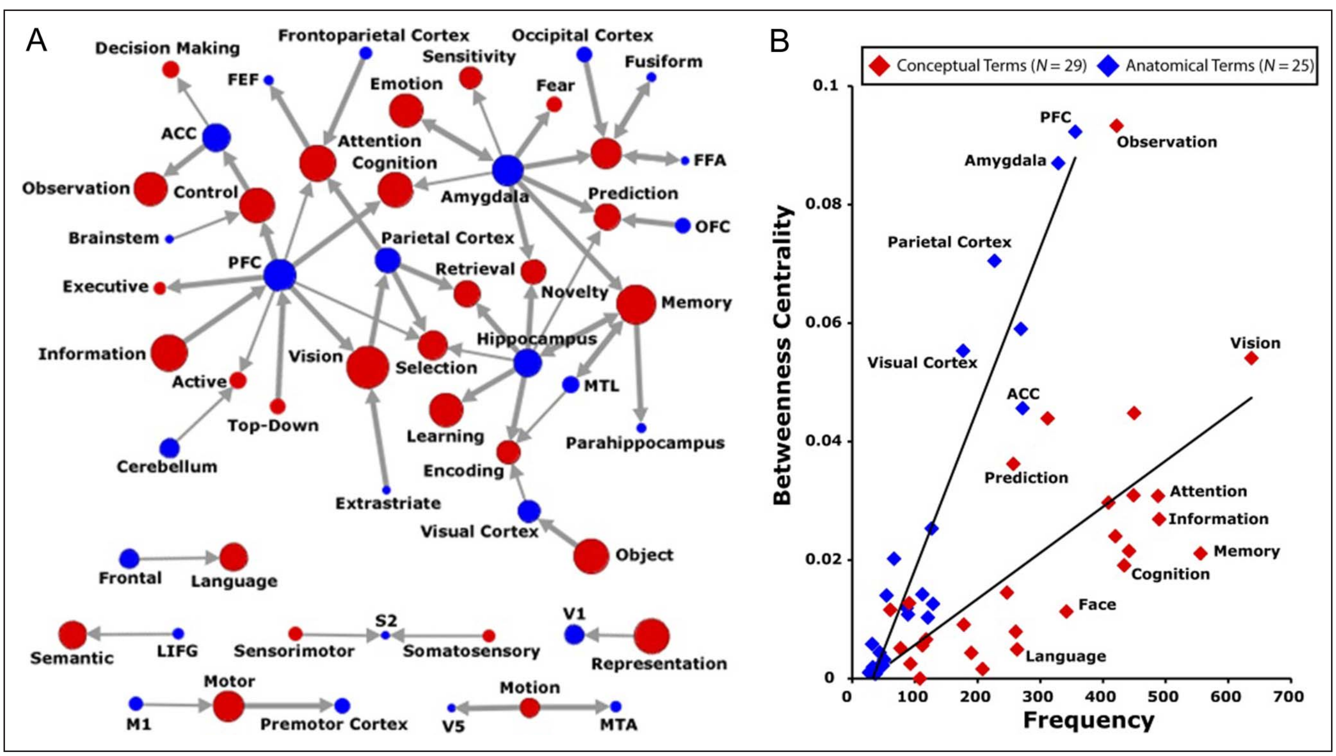
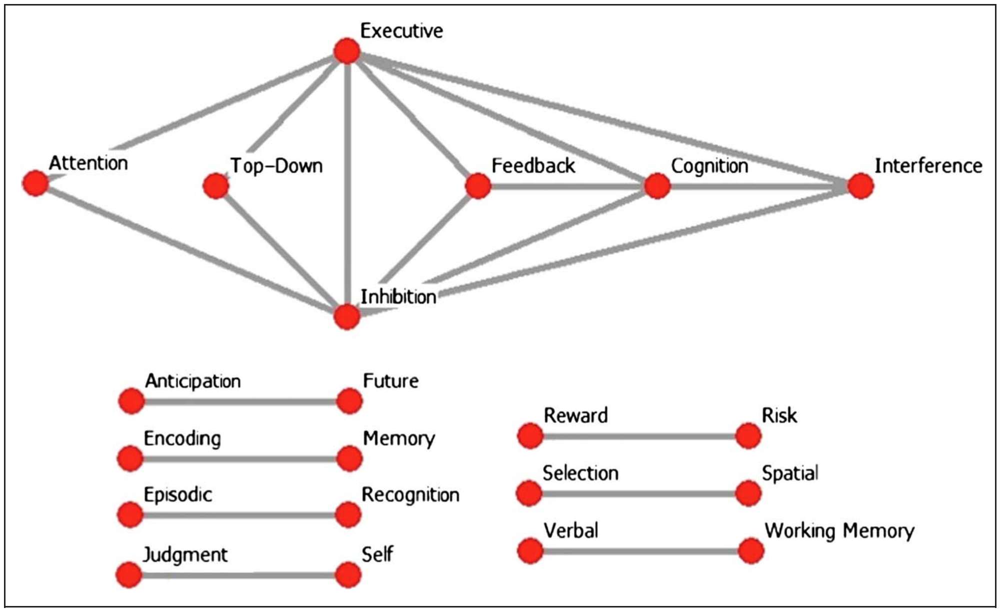


Figure 3. Functional Network of links between concept and anatomical terms. (A) Network visualization representing the interconnection between conceptual (red) and anatomical (blue) terminology used in the field of cognitive neuroscience (density = 0.04). The top 54 strongest linked terms as determined by a link weighting threshold (>12). (B) Plot of betweenness centrality versus frequency for the 54 anatomical terms visualized. Anatomy terms have steeper linear regression slopes, indicating the anatomical terms have higher betweenness centrality than conceptual terms and suggesting that information about anatomy contributes more than information about concepts in defining the overall structure of the Functional Network.

Figure 4. Map of structural similarity for the Conceptual Network. Shown are the top 21 concept nodes of the second-order Conceptual Network, thresholded at link weight 0.70. Link terms occupy similar places in the network and therefore represent semantic synonyms.



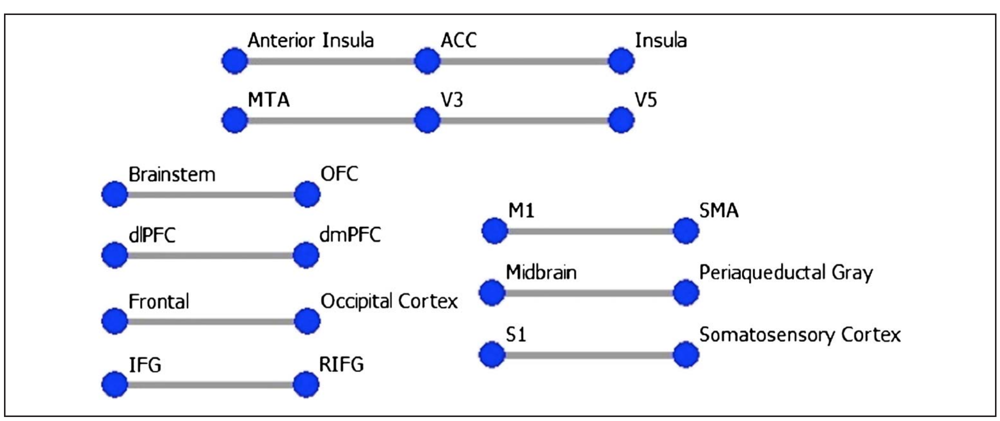
similarity between each node in the first-order network (Figures 4–6). Links indicate terms that occupy similar positions in a network and therefore represent semantic synonyms. For example, in the second-order functional network, two concepts might be linked because they reliably engage the same brain regions, because they are used interchangeably to describe a mental process, or both. Identifying such similarities is important because they suggest aspects of the literature that deserve further refinement, either through creation of a new superordinate category or through the purging of unneeded synonyms. Here, we highlight some key examples of terms occupying similar places in the networks.

Analyses of the conceptual and anatomical maps revealed numerous small groups of terms that carry relatively similar meaning (e.g., *future* and *anticipation*) or that come from the same circumscribed area of the literature (e.g., *reward* and *risk*). More intriguing were several larger groups of terms that were highly interconnected. The single largest grouping in any analysis comprised seven concept terms that all described aspects of control processing (e.g., *top–down*, *executive*, *inhibition*), indicating that this topic area contains a number of highly similar concepts that remain imperfectly distinguished from each other. There was also a notable group of anatomical terms that clearly define distinct regions (e.g., *anterior insula*, *thalamus*), but that share the property of being connected to a wider range of cortical regions. This not only provides additional evidence for the characterization of these regions as important building links within the discipline but also argues that new research has room to further elaborate their distinct roles in processing.

DISCUSSION

Cognitive neuroscience, despite its relative youth as a discipline, now evinces a well-defined semantic structure of brain-to-behavior mappings. Traditional meta-analytic

Figure 5. Map of structural similarity for the Anatomical Network. The top 20 anatomy nodes, link weight greater than 0.73, are displayed for the second-order Anatomical Network.



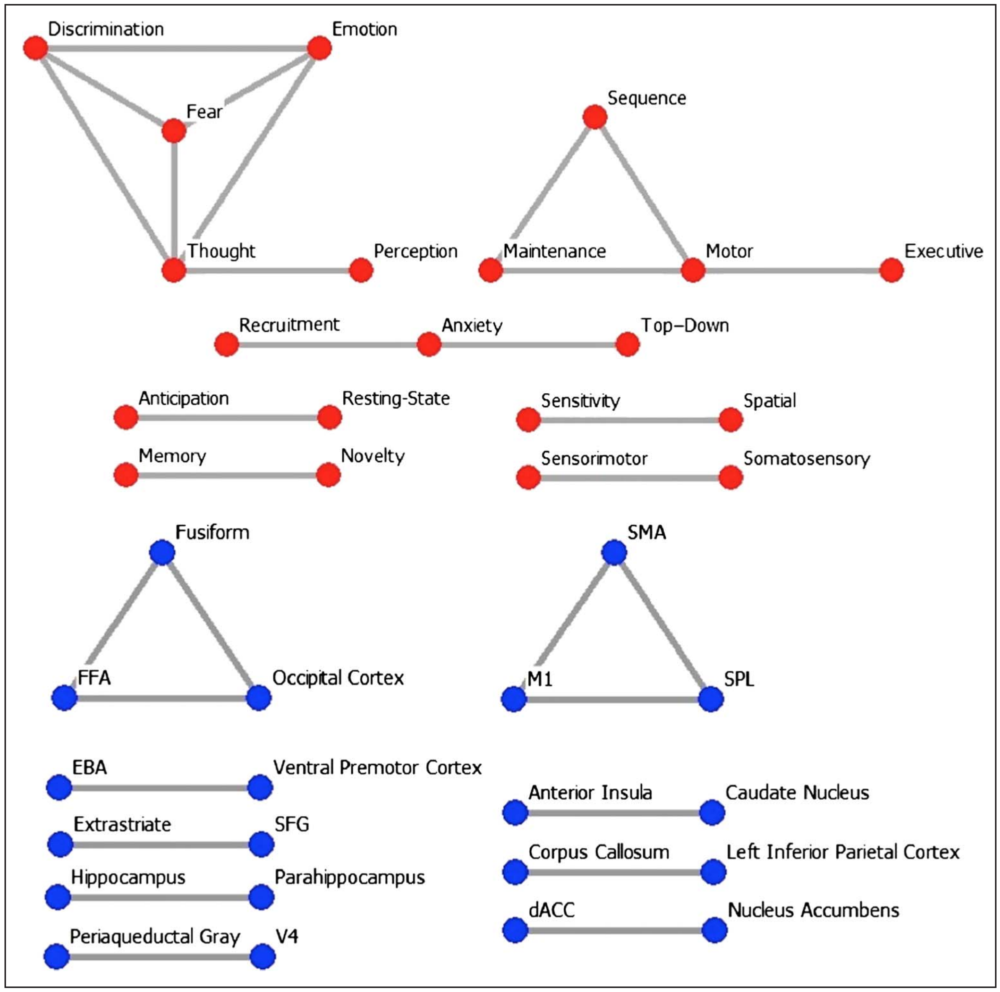


Figure 6. Map of structural similarity for the Functional Network. Relative structural similarity was visualized separately for concept nodes (red) and anatomy nodes (blue) of the Functional Network. The second-order Conceptual Network revealed 20 nodes above a link weight threshold of 0.71; the second-order Anatomical Network shows 20 nodes above a threshold of 0.66. Nodes connected in these networks have structural similarity in how they connect to the other node class.

approaches focus on the quantitative consistency of specific research findings (e.g., activation likelihood estimation) or on the connections among different topics (e.g., ontologies) and researchers (e.g., citation analyses). Our approach, in contrast, characterizes how cognitive neuroscience presents itself to the larger scientific community, through the summaries of individual articles within their titles and abstracts. Cognitive neuroscience is well matched to this approach: It has become a linking discipline that now constructs numerous bridges between the brain structures studied by neuroscience and the constructs created by psychology (Bassett & Gazzaniga, 2011; Gonsalves & Cohen, 2010; Shimamura, 2010). The core challenge for cognitive neuroscience, at present, is synthesizing across those many links—it must distill its massive and rapidly expanding literature into smaller sets of core principles.

Semantic analyses, like those in the current project, identify structural properties within a corpus in a data-driven and largely endogenous manner. Constructing a corpus from abstracts, however, poses challenges because no abstract perfectly recapitulates its source experiment. Instead, authors construct an abstract through some complex combination of the experimental results, the filtering of those results by perceived importance, their own rhetorical and semantic goals, and disciplinary considerations that shape how topics are chosen and reported (Samraj, 2005; Lores, 2004). Authors may specify terms to varying degrees depending on where they choose to draw anatomical or theoretical boundaries, altering the shape of the semantic structure at the level of individual nodes. To avoid imposing an additional layer of subjectivity by selecting terms based on expert opinion alone, we applied thresholds to sift out the most frequent terms in the literature for inclusion in the word lists used to generate the networks.

Moreover, the co-occurrence of two concepts within a particular abstract could reflect a positive association, a negative association, or even a speculation about the need for future research. A similar uncertainty is seen in co-citation analyses, such that a given article may be cited both by articles that agree with and that disagree with its findings. Yet, the very pairing of two concepts still provides important information, even considering the above limitations. For example, when individuals query internet search engines like Google, typical search strings involve simple juxtaposition of terms, not operators that qualify their relationships—and the search engines will return pages that contain those terms regardless of their semantic relationship. The corpus (in this analogy, internet content) has an underlying structure that facilitates extraction of valuable information. Thus, despite their limitations, these network analyses allow quantification of the relationships among concepts that have broad prevalence as well as how those concepts combine into semantic networks. Future applications that account for these rhetorical associations may yield deeper insight into the knowledge structures under scrutiny.

Negative Structure: Bridging Islands and Filling Gaps

A powerful feature of semantic network analysis is that it can identify inefficiencies in network structure, as when a local region of the network has more or fewer connections than expected based on the overall network statistics (Evans & Foster, 2011). Our analyses indicate that the current cognitive neuroscience literature contains two sorts of inefficiencies, which we colloquially label "islands" and "gaps."

The islands in each of our maps are visually obvious as small groups of terms whose connectedness is much greater within their own group than to the main body of the network. Islands are not in themselves problematic; in fact, for biological systems, the restricted milieu of an island may be an important contributor to accelerated evolution (Millien, 2006). Similarly, the (metaphorical) islands in our network may indicate new semantic distinctions between concepts that can lead to a specialized subdiscipline where research can proceed more rapidly than in the main discipline. Over time, reestablishment of connections to the larger network will provide channels for reentrant flow of novel findings. Consider the prominent island of concepts terms from economics (see Figure 1A). Over the past decade, research on the neural basis of decision-making has progressed largely apace from cognitive neuroscience, in large part because of its focus on economic decision variables rather than psychological processes. The result has been a small, high-profile literature that shares methods, but not conceptual frameworks, with research on other aspects of cognition. Yet, even this clear island shows evidence of coming closer to the mainland. Mainstream work on models of cognitive control in prefrontal cortex now connects to neuroeconomic studies of self-control in decision-making; conversely, information about potential rewards is now recognized as having broad effects throughout the brain (Vickery, Chun, & Lee, 2011), influencing basic functions of perception (Serences, 2008) and memory (Han, Huettel, Raposo, Adcock, & Dobbins, 2010). In essence, new bridges are being built to all three divisions of the cognitive network. One natural prediction, accordingly, is that neuroeconomics will become more, not less integrated into cognitive neuroscience over the coming years (Levallois et al., 2012).

The gaps in each network are not obvious from its visual structure, but they can be appreciated from the network statistics: terms with high betweenness centrality relative to their frequency. Key examples from the Anatomical Network include *insula* and *thalamus*, each of which was much less frequent but more central than terms like *amygdala*, *hippocampus*, and *parietal cortex*. Within the Conceptual Network, process terms like *selection*, *emotion*, and *control* are more central than, but not as frequent as, domain terms like *vision*, *memory*, and *reward*. Additional research on gap terms like *insula* would have the effect of strengthening connections between disparate parts of the network, which in turn would increase the coherence of the discipline. Conversely, a continuing focus on high-frequency, low-centrality terms risks creating subdisciplinary islands. Collectively the positive and negative structures illustrated in these examples reveal instances where topics are over- or underrepresented and can be used to indicate areas of research that might be pursued most profitably.

Positive Structure: Conceptual Hubs and Anatomical Branches

From the vantage point provided by semantic network analyses, several unexpected structural features are evident. In particular, psychological concepts and anatomical terms have qualitatively and quantitatively distinct organizations. Conceptual terms are organized around a central hub with three primary divisions: perception/attention, representation, and control. In contrast, no such core exists for the anatomical network. Rather, the structure of this network is dominated by a few frequent and densely interconnected terms, which feed into long branches associated with individual processing streams. Anatomical terms also have higher betweenness centrality than conceptual terms within the Functional Network; this means that the structure of that network tends to be driven by a small set of anatomical terms.

Historical and rhetorical factors likely shape the different roles that conceptual and anatomical terms play within the cognitive neuroscience literature (Mays & Jung, 2012; Jack & Appelbaum, 2010). The semantic organization of psychological concepts builds on more than one hundred years of academic history, which in turn grew out of the ancient and intuitive interest in how our minds work. The Conceptual Network (Figure 1A) recapitulates the long-standing division of the mind into stages of information processing: perceiving something, representing it in memory, and then controlling behavior accordingly. In contrast, cognitive neuroscience itself has shaped how modern neuroscience organizes brain anatomy. Traditional core elements of brain structure (e.g., the brainstem, hypothalamus) are simply absent from the Anatomical Network (Figure 2B). Replacing them are new divisions of the cerebral cortex identified both anatomically (e.g., *anterior insula*) and functionally (e.g., *fusiform face area*). If cognitive neuroscience's core goal is to reconcile models of the mind and brain, then progress toward that goal will cause these two networks to come more into alignment. A natural prediction, therefore, is that the single-brain-region terms that now dominate the current literature will gradually be replaced by systems-level descriptions (e.g., *default network*). Cognitive neuroscience, accordingly, will treat information processing as arising not from individual brain regions interacting along a unidirectional path but from sets of local networks that jointly support complex cognition.

Appendix 1. Concept Terms, Frequencies, and Centralities

Rank	*Term*	*Frequency*	*Conceptual Betweenness*	*Functional Betweenness*
1	vision	637	0.0209	0.0541
2	memory	556	0.0196	0.0211
3	behavior	497	0.0705	0.0224
4	information	490	0.0129	0.0269
5	attention	488	0.0116	0.0308
6	representation	450	0.0272	0.0448
7	control	449	0.0455	0.0309
8	object	442	0.0083	0.0215
9	perception	439	0.0182	0.026
10	cognition	434	0.0525	0.0191
11	observation	422	0.0217	0.0933
12	learning	420	0.0523	0.024
13	emotion	409	0.0536	0.0297
14	action	365	0.0224	0.019
15	motor	344	0.0074	0.0398
16	face	342	0.022	0.0113
17	word	339	0.0404	0.005
18	reward	319	0.0164	0.0067
19	selection	312	0.0515	0.0439
20	movement	282	0.0318	0.0064
21	language	263	0.0095	0.0049
22	semantic	261	0.0103	0.0079
23	prediction	257	0.024	0.0362
24	auditory	252	0.0208	0.0117
25	spatial	250	0.0431	0.007
26	retrieval	247	0.0083	0.0145
27	speech	240	0.0119	0.0047
28	target	240	0.0078	0.0099
29	social	230	0.0076	0.0048
30	working_memory	228	0.0177	0.0134
31	pain	217	0.0173	0.0046

Appendix 1. (*continued*)

Rank	*Term*	*Frequency*	*Conceptual Betweenness*	*Functional Betweenness*
32	novelty	208	0.0127	0.0016
33	inhibition	204	0.0285	0.0109
34	sensory	200	0.0221	0.0082
35	decision	192	0.0152	0.01
36	encoding	190	0.0219	0.0043
37	error	181	0.0204	0.0148
38	recognition	181	0.043	0.0124
39	sensitivity	178	0.0276	0.0091
40	image	170	0.0193	0.0037
41	outcome	153	0.0273	0.0042
42	risk	149	0.0026	0.002
43	category	147	0.0119	0.0024
44	adaptation	143	0.0237	0.0103
45	judgment	139	0.017	0.0011
46	mental	138	0.0201	0.0051
47	sentence	137	0.0097	0.0022
48	choice	125	0.0197	0.0061
49	shape	122	0.0174	0.0007
50	motion	118	0.0083	0.0066
51	decision_making	112	0.0122	0.0056
52	feedback	111	0.0205	0.0032
53	repetition	110	0.0074	0.007
54	active	108	0.0115	0
55	episodic	106	0.0126	0.003
56	reading	106	0.0159	0.0003
57	understanding	105	0.0045	0.0038
58	verbal	101	0.0116	0.0011
59	ability	99	0.0228	0.0004
60	sequence	99	0.0144	0.0012
61	sound	95	0.0009	0.0001
62	monitoring	94	0.0294	0.0022
63	fear	93	0.003	0.0025
64	scene	93	0.0068	0.0035
65	schizophrenia	93	0.0146	0.0001
66	top–down	91	0.0067	0.0127
67	detection	90	0.0124	0.0089
68	organization	90	0.0093	0.0062
69	affective	83	0.025	0.0019

Appendix 1. (*continued*)

Rank	*Term*	*Frequency*	*Conceptual Betweenness*	*Functional Betweenness*
70	discrimination	83	0.036	0.0022
71	phonological	83	0.0024	0.0012
72	knowledge	80	0.0153	0.0017
73	resting	78	0.0045	0.0028
74	sensorimotor	77	0.0052	0.0051
75	suppression	76	0.0177	0.0034
76	priming	73	0.0256	0.0005
77	future	71	0.0028	0.0018
78	executive	69	0.0068	0.0038
79	development	67	0.0056	0.0002
80	thought	66	0.0172	0.0012
81	training	66	0.0029	0.0024
82	interest	64	0.024	0.0065
83	difficulty	62	0.0111	0.0004
84	load	62	0.008	0.0036
85	anticipation	61	0	0.0011
86	interference	61	0.0385	0.0003
87	somatosensory	61	0.0066	0.0116
88	spontaneous	60	0.0074	0.0006
89	anxiety	59	0.0002	0.0005
90	self	59	0.0044	0.0001
91	acquisition	58	0.0014	0.0002
92	recruitment	58	0.0043	0.0019
93	identification	55	0.0133	0.002
94	competition	54	0.0137	0.0008
95	resting-state	54	0.013	0.0001
96	lexical	52	0.0011	0.0006
97	simultaneous	52	0	0.0002
98	maintenance	51	0.0064	0.0011
99	execution	50	0.0012	0.0002
100	moral	50	0.0025	0.0005

The top 100 concept terms used in the generation of the meta-network. Terms are sorted by frequency and listed with betweenness centrality values for each term when it appeared in the Conceptual Network and in the Functional Network.

Appendix 2. Anatomy Terms, Frequencies, and Centralities

Rank	*Term*	*Frequency*	*Anatomical Betweenness*	*Functional Betweenness*
1	prefrontal_cortex (PFC)	356	0.0618	0.0923
2	amygdala	329	0.0432	0.087
3	anterior_cingulate_cortex (ACC)	272	0.0401	0.0456
4	hippocampus	269	0.039	0.059
5	parietal_cortex	227	0.0357	0.0705
6	visual_cortex	177	0.0087	0.0553
7	intraparietal_sulcus	152	0.0291	0.0227
8	medial_prefrontal_cortex (mPFC)	138	0.0168	0.0211
9	insula	131	0.0839	0.0225
10	cerebellum	129	0.0614	0.0126
11	inferior_frontal_gyrus	128	0.033	0.0242
12	frontal	127	0.0683	0.0253
13	primary_visual_cortex (V1)	121	0.0132	0.0103
14	medial_temporal_lobe (MTL)	112	0.0134	0.0142
15	thalamus	101	0.1058	0.0115
16	dorsolateral_prefrontal_cortex (dlPFC)	97	0.0834	0.0199
17	precuneus	93	0.0684	0.0033
18	striatum	91	0.0074	0.0196
19	premotor_cortex	90	0.078	0.0153
20	orbitofrontal_cortex (OFC)	89	0.0197	0.0108
21	superior_temporal_sulcus	88	0.0199	0.0156
22	occipital_cortex	87	0.0776	0.0119
23	supplementary_motor_area (SMA)	84	0.0494	0.0024
24	temporoparietal_junction (TPJ)	81	0.0197	0.0106
25	posterior_parietal_cortex	80	0.0004	0.0076
26	basal_ganglia	79	0.0031	0.0036
27	inferior_parietal_lobule	79	0.0327	0.0093
28	superior_temporal_gyrus	79	0.0183	0.0096
29	posterior_cingulate_cortex	75	0.0223	0.0013
30	frontal_cortex	73	0.0893	0.0267
31	primary_motor_cortex (M1)	73	0.0002	0.0022
32	primary_somatosensory_cortex (S1)	72	0.0112	0.0035
33	frontoparietal_cortex	67	0.0765	0.0202
34	subcortical	65	0.0131	0.0034
35	putamen	64	0.0459	0.0043
36	ventromedial_prefrontal_cortex (vmPFC)	64	0.0039	0.0049
37	auditory_cortex	63	0.0077	0.0096
38	left_inferior_frontal_gyrus (LIFG)	55	0.0022	0.014

Appendix 2. (*continued*)

Rank	*Term*	*Frequency*	*Anatomical Betweenness*	*Functional Betweenness*
39	ventrolateral_prefrontal_cortex (vlPFC)	53	0	0.004
40	middle_temporal_area (MTA)	51	0.022	0.0032
41	ventral_striatum	50	0.0124	0.0045
42	fusiform_gyrus	49	0.034	0.0047
43	parahippocampus	49	0.0132	0.0022
44	temporal_cortex	49	0.0221	0.0103
45	fusiform	47	0.0188	0.0025
46	nucleus_accumbens	47	0	0.0014
47	anterior_insula	45	0.0304	0.0015
48	frontal_eye_field (FEF)	44	0.0034	0.0044
49	inferior_parietal_cortex	44	0.0107	0.0055
50	middle_temporal_gyrus	43	0.0023	0.0054
51	dorsal_anterior_cingulate_cortex (dACC)	42	0.0012	0.0026
52	midbrain	41	0.0012	0.0021
53	limbic_system	40	0.0071	0.0058
54	mirror_neuron_system	40	0	0.0032
55	caudate	39	0.0368	0.0011
56	brainstem	38	0.0011	0.0008
57	motor_cortex	37	0.0046	0.0035
58	secondary_somatosensory_cortex (S2)	36	0.0037	0.0008
59	visual_area_3 (V3)	36	0.0086	0.0006
60	cingulate	35	0.0084	0.0064
61	cingulate_cortex	33	0.0298	0.0059
62	dorsal_premotor_cortex	33	0.0193	0.0004
63	fusiform_face_area (FFA)	33	0.0023	0.0019
64	dorsomedial_prefrontal_cortex (dmPFC)	32	0.0029	0.0017
65	extrastriate	32	0.0084	0.0058
66	angular_gyrus	31	0.0011	0.0003
67	brocas_area	30	0.0071	0.0074
68	middle_frontal_gyrus	28	0.006	0
69	parahippocampal_place_area (PPA)	27	0.0053	0.0017
70	posterior_superior_temporal_sulcus	27	0	0.0008
71	somatosensory_cortex	27	0	0.0008
72	visual_area_5 (V5)	27	0.0107	0.001
73	lateral_prefrontal_cortex (lPFC)	26	0.0361	0.0088
74	left_inferior_parietal_cortex	26	0.0097	0.0005
75	periaqueductal_gray	24	0.0002	0.0002
76	temporal_gyrus	24	0.0164	0.0023

Appendix 2. (*continued*)

Rank	Term	Frequency	Anatomical Betweenness	Functional Betweenness
77	pre-supplementary_motor_area (pre-SMA)	23	0.0639	0.0008
78	secondary_visual_area (V2)	23	0	0.0002
79	caudate_nucleus	22	0.0165	0.0054
80	extrastriate_body_area (EBA)	22	0.001	0.0001
81	visual_area_4 (V4)	21	0.0001	0.0006
82	early_visual_cortex	20	0.0001	0.001
83	inferior_temporal_cortex	20	0.0191	0.002
84	right_inferior_frontal_gyrus (RIFG)	20	0.0143	0.0014
85	occipitotemporal_cortex	19	0.0206	0.0025
86	superior_frontal_gyrus	19	0.0045	0.0004
87	visual_system	19	0	0.0016
88	corpus_callosum	18	0	0.0002
89	hypothalamus	18	0	0.0013
90	parahippocampal_gyrus	18	0.0188	0.0001
91	perirhinal_cortex	18	0	0.0029
92	supramarginal_gyrus	18	0.0051	0.0004
93	lateral_parietal_cortex	17	0.0002	0.0002
94	rostrolateral_prefrontal_cortex (rlPFC)	17	0	0.0006
95	superior_parietal_lobule	17	0.0085	0.0002
96	precentral_gyrus	16	0.0388	0.0001
97	ventral_premotor_cortex	16	0.0009	0.0001
98	heschls_gyrus	15	0	0
99	posterior_insula	15	0.0022	0.0002
100	temporal_sulcus	15	0.0101	0

The top 100 anatomy terms used in the generation of the metanetwork. Terms are sorted by frequency and listed with betweenness centrality values for each term when it appeared in the Anatomical Network and in the Functional Network. Labels used for visualizing the nodes are indicated in parentheses, where applicable.

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REFERENCES

Bassett, D. S., & Gazzaniga, M. S. (2011). Understanding complexity in the human brain. *Trends in Cognitive Sciences, 15,* 200–209.

Behrens, T. E. J., Fox, P., Laird, A., & Smith, S. M. (2013). What is the most interesting part of the brain? *Trends in Cognitive Sciences, 17,* 2–4.

Borgatti, S. P., Everett, M. G., & Freeman, L. C. (2002). *UCINET 6 for Windows: Software for social network analysis* (Version 6.311) [Software]. Retrieved from www.analytictech.com/.

Bruer, J. T. (2004). Mapping cognitive neuroscience: Two-dimensional perspectives on twenty years of cognitive neuroscience research. In M. S. Gazzaniga (Ed.), *Cognitive neurosciences IV* (pp. 1–45). Cambridge, MA: MIT Press.

Bruer, J. T. (2010). Can we talk? How the cognitive neuroscience of attention emerged from neurobiology and psychology, 1980-2005. *Scientometrics, 83,* 751–764.

Burright, M. A., Hahn, T. B., & Antonisse, M. J. (2005). Understanding information use in a multidisciplinary field: A local citation analysis of neuroscience research. *College & Research Libraries, 66,* 198–210.

Carley, K. M. (1997). Network test analysis: The network position of concepts. In C. W. Roberts (Ed.), *Text analysis and the social sciences* (pp. 79–102). Mahwah, NJ: Erlbaum.

Carley, K. M. (2010a). *Automap* (Version 3.0.3) [Software]. Retrieved from www.casos.cs.cmu.edu/.

Carley, K. M. (2010b). *Organization Risk Analyzer* (Version 2.0.7) [Software]. Retrieved from www.casos.cs.cmu.edu/.

Carley, K. M., & Reminga, J. (2004). *ORA: Organization Risk Analyzer*. CASOS Technical Report, CMU-ISRI-04-106, 1–45.

Diesner, J., & Carley, K. M. (2004). *AutoMap1.2: Extract, analyze, represent, and compare mental models from texts*. CASOS Technical Report, CMU-ISRI-04-100, 1-26.

Diesner, J., & Carley, K. M. (2005). Revealing social structure from texts: Meta-matrix text analysis as a novel method for network text analysis. In V. K. Narayanan & D. J. Armstrong (Eds.), *Causal mapping for information systems and technology research: Approaches, advances, and illustrations* (pp. 1–35). Harrisburg, PA: Idea Group Publishing.

Evans, J. A., & Foster, J. G. (2011). Metaknowledge. *Science, 331,* 721–725.

Freeman, L. C. (1977). A set of measures of centrality based on betweenness. *Sociometry, 40,* 35–41.

Gonsalves, B. D., & Cohen, N. J. (2010). Brain imaging, cognitive processes, and brain networks. *Perspectives on Psychological Science, 5,* 744–752.

Han, S., Huettel, S. A., Raposo, A., Adcock, R. A., & Dobbins, I. G. (2010). Functional significance of striatal responses during episodic decisions: Recovery or goal attainment? *Journal of Neuroscience, 30,* 4767–4775.

Jack, J., & Appelbaum, L. G. (2010). This is your brain on rhetoric: Research direction for neuroscience. *Rhetorical Society Quarterly, 40,* 411–437.

Levallois, C., Clithero, J. A., Wouters, P., Smidts, A., & Huettel, S. A. (2012). Translating upwards: Linking the neural and social sciences via neuroeconomics. *Nature Reviews Neuroscience, 13,* 789–797.

Lores, R. (2004). On RA abstracts: From rhetorical structure to thematic organisation. *English for Specific Purposes, 23,* 280–302.

Mays, C., & Jung, J. (2012). Priming terministic inquiry: Toward a methodology of neurorhetoric. *Rhetoric Review, 31,* 41–59.

Mehl, R. M. (2005). Quantitative text analysis. In M. Eid & E. Diener (Eds.), *Handbook of multimethod measurements in psychology* (pp. 141–156). Washington, DC: American Psychological Association.

Millien, V. (2006). Morphological evolution is accelerated among island mammals. *PLoS Biology, 4,* e321.

Moody, C. J., & Light, R. (2006). A view from above: The evolving sociological landscape. *The American Sociologist, 37,* 67–86.

Nielsen, F. A. (2009). Visualizing data mining results with the brede tools. *Frontiers in Neuroinformatics, 3,* 26.

Poldrack, R. (2010). Mapping mental function to brain structure: How can cognitive neuroimaging succeed? *Perspectives on Psychological Science, 5,* 753–761.

Poldrack, R. A., Kittur, A., Kalar, D., Miller, E., Seppa, C., Gil, Y., et al. (2011). The cognitive atlas: Toward a knowledge foundation for cognitive neuroscience. *Frontiers in Neuroinformatics, 5,* 17.

Popping, R. (2000). *Computer-assisted text analysis*. London: Sage Publications.

Robins, R. W., Gosling, S. D., & Craik, K. H. (1999). An empirical analysis of trends in psychology. *The American Psychologist, 54,* 117–128.

Samraj, B. (2005). An exploration of a genre set: Research article abstracts and introductions in two disciplines. *English for Specific Purposes, 24,* 141–156.

Serences, J. T. (2008). Value-based modulations in human visual cortex. *Neuron, 60,* 1169–1181.

Shiffrin, R. M., & Borner, K. (2004). Mapping knowledge domains. *Proceedings of the National Academy of Sciences, U.S.A., 101(Suppl. 1),* 5183–5185.

Shimamura, A. P. (2010). Bridging psychological and biological science: The good, bad, and ugly. *Perspectives on Psychological Science, 5,* 772–775.

Smith, D. V., & Huettel, S. A. (2010). Decision neuroscience: Neuroeconomics. *Wiley Interdisciplinary Reviews: Cognitive Neuroscience, 1,* 854–871.

Van Essen, D. C. (2009). Lost in localization—But found with foci?! *Neuroimage, 48,* 14–17.

Vickery, T. J., Chun, M. M., & Lee, D. (2011). Ubiquity and specificity of reinforcement signals throughout the human brain. *Neuron, 72,* 166–177.

Viedma-del-Jesus, M. I., Perakakis, P., Munoz, M. A., Lopez-Herrera, A. G., & Vila, J. (2011). Sketching the first 45 years of the journal *Psychophysiology* (1964-2008): A co-word-based analysis. *Psychophysiology, 48,* 1029–1036.

Yarkoni, T., Poldrack, R. A., Nichols, T. E., Van Essen, D. C., & Wager, T. D. (2011). Large-scale automated synthesis of human functional neuroimaging data. *Nature Methods, 8,* 665–670.

Yarkoni, T., Poldrack, R. A., Van Essen, D. C., & Wager, T. D. (2010). Cognitive neuroscience 2.0: Building a cumulative science of human brain function. *Trends in Cognitive Sciences, 14,* 489–496.