Available online at www.sciencedirect.com

ScienceDirect

ELSEVIER

Current Opinion in Behavioral Sciences

Predicting attention across time and contexts with functional brain connectivity

Hayoung Song[1] and Monica D Rosenberg[1,2]

The ability to sustain attention differs across people and varies over time within a person. Models based on patterns of static functional brain connectivity observed during task performance and rest show promise for predicting individual differences in sustained attention as well as other forms of attention. The sensitivity of connectome-based models to attentional state changes, however, is less well characterized. Here, we review recent evidence that time-varying functional brain connectivity predicts fluctuations in attention in controlled and naturalistic task contexts. We propose that building connectome-based models to predict changes in attention across multiple timescales and experimental contexts can help further disentangle state versus trait influences on functional connectivity patterns, elucidate the behavioral relevance of functional connectivity dynamics, and contribute to the development of a comprehensive suite of generalizable neuromarkers of attention. To achieve this goal, we suggest collecting multi-task, multi-session neuroimaging samples with concurrent behavioral and physiological measures of attentional state.

Addresses
[1] Department of Psychology, University of Chicago, United States
[2] Grossman Institute for Neuroscience, Quantitative Biology and Human Behavior, University of Chicago, United States

Corresponding authors:
Song, Hayoung (hyssong@uchicago.edu), Rosenberg, Monica D (mdrosenberg@uchicago.edu)

Current Opinion in Behavioral Sciences 2021, **40**:33–44

This review comes from a themed issue on **Deep imaging - personalized neuroscience**

Edited by **Caterina Gratton** and **Rodrigo M Braga**

For a complete overview see the Issue and the Editorial

Available online 29th January 2021

https://doi.org/10.1016/j.cobeha.2020.12.007

Introduction

People differ in how well they sustain attention. Whereas some individuals can attend to a task for long periods of time, others lose focus more quickly and more often. What aspects of brain function distinguish those of us with better and worse sustained attention function? Work has revealed that models based on a person's unique functional brain connectivity 'fingerprint', or pattern of statistical dependence between brain regions' neuroimaging signal fluctuations [1], predict aspects of their attention function including sustained attention [2–4], attentional control [5,6], distractor suppression [7], and attentional blink task performance [8]. Model predictions can be generated from functional magnetic resonance imaging (fMRI) data collected during different cognitive tasks as well as during rest, when participants are simply instructed to lie still in the scanner and (often but not always) view a centrally presented fixation cross.

These trait-like attention predictions, however, don't tell the whole story. Unlike fingerprints, functional connectivity patterns change over time. Attention function also varies, fluctuating from moment to moment with, for example, distraction, depletion, mind wandering, motivation, and engagement. Whether functional connectivity dynamics are related to ongoing cognitive and attentional state dynamics, however, is a topic of significant debate. On one hand, work suggests that functional brain network organization is dominated by trait variance [9,10••], that functional connectivity dynamics are driven by noise and sampling variability [11,12], and that functional connectivity observed at relatively short times scales (such as tens of minutes) does not meet standard measures of reliability [13]. On the other hand, there is evidence that functional networks reconfigure during tasks with different attentional, perceptual, and cognitive demands [14••,15] and pharmacological intervention [16,17••]. Furthermore, evidence suggests that functional connectivity measured at short time scales (tens of seconds) predicts task state [18] and ongoing task performance [17••], and that relationships between functional connectivity and changes in attention task performance are observable with intracranial electroencephalography [19•].

How do we reconcile the need for collecting significant amounts of data to measure what are, primarily, stable person-specific functional connectivity patterns with the growing evidence for robust and replicable relationships between functional connectivity dynamics and internal state dynamics? Here we review work on connectome-based predictors of individual differences in attention and changes in attention over time. We focus on sustained attention (also known as tonic alertness), the ability maintain focus on a task or stimulus for a prolonged period of time [20–22]. We hypothesize that sustained attention fluctuations during task, rest, and naturalistic contexts are ubiquitous but underappreciated, and may explain variance in within-person changes in functional connectivity that, without sufficiently sensitive behavioral or physiological measures of attentional state to validate them, may otherwise be characterized as noise. To test this hypothesis, we propose collecting multi-task, multi-session samples with concurrent behavioral and physiological measures of attentional state (Figure 1). Dense longitudinal phenotyping of brain and behavioral data can help resolve the apparent tension between mounting evidence for both stable network architecture and cognitively meaningful network dynamics, and help disentangle state-like from trait-like aspects of functional brain organization.

Predicting individual differences in sustained attention

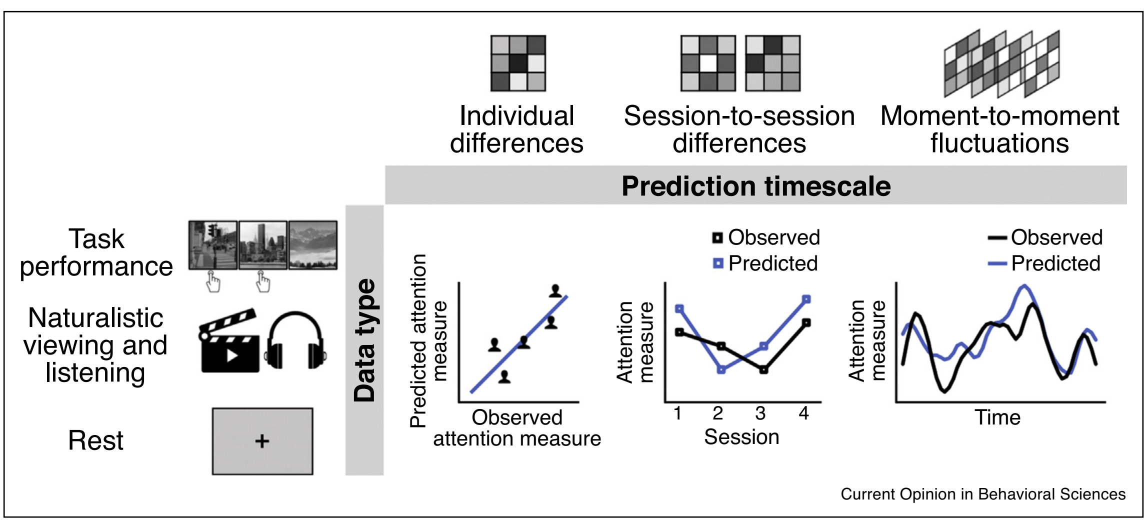
Although there is a rich history of individual differences research in cognitive psychology, cognitive neuroscience research has traditionally characterized group-average features of, or group-level differences in, brain structure and function. However, with the growing availability of large open-source neuroimaging datasets and advances in resting-state fMRI and predictive modeling, scholars have begun to characterize patterns of brain activity and connectivity that predict individual differences in behavior [23–26] (see Box 1).

A catalyst of work predicting individual differences from functional brain connectivity was the discovery that an individual's functional connectivity pattern is stable and unique enough to serve as a 'fingerprint' that can identify them from a group [1,27] and thus may be useful for predicting trait-like aspects of behavior. Since then, work has suggested that functional connectivity patterns not only serve as individual identifiers but also predict phenotypes including fluid intelligence [1,28], sustained attention [4], working memory [29–31], personality traits [32–34], and clinical symptoms [35–37].

Box 1 Large, open-source neuroimaging datasets.

With recent norm-shifts in cognitive neuroscience and psychology towards data, code, and model sharing and big data approaches [81–83], repositories are open-sourcing a large number of individuals' [84], or dense longitudinal sampling of several individuals' [14••,85], neuroimaging data. In these samples, data are collected as participants perform different psychological tasks [86], watch movies or listen to stories [87–90], or simply rest inside the scanner. The Human Connectome Project [91] and Adolescent Brain Cognitive Development Study [92], for example, include multiple imaging sessions and tasks per participant along with out-of-scanner measures including behavioral assessments and questionnaires. Such open-source datasets have facilitated significant advances in the construction of models that predict individual differences in behavior from brain activity and connectivity patterns. Complementary work is beginning to pursue prediction of changes in cognitive and attentional processes over time—from high-frequency fluctuations within a single scan session to developmental change across months and years—using these large datasets.

Figure 1



Predicting attention across time and contexts from multi-session neuroimaging.
Connectome-based models of sustained attention can be trained and tested on neuroimaging data collected during different scan conditions, including task performance, naturalistic viewing and listening, and rest. Training models on one data type and testing on another can inform the degree to which sustained attention modeled during a single context generalizes to (or differs from) sustained attention characterized in other contexts. Predictive modeling can be performed across different timescales. Depending on the research question, models can be applied to one measure of functional connectivity per person to predict differences in attentional abilities between people (plot 1), or to multiple measures of functional connectivity per person to predict changes in attention over time within a person (plots 2–3). Multiple measures of connectivity can be calculated from fMRI data collected during different scan sessions, runs, tasks, and task blocks (plot 2), as well as from time windows within these periods to capture higher-frequency attention fluctuations (plot 3). Measures of attentional state depend on scan condition, and may include ongoing task performance, eye-tracking measures, and self-reported engagement or mind wandering.

An early example of connectome-based predictions of individual differences asked how functional network organization relates to individual differences in sustained attention [4]. To address this question, researchers used fMRI data collected during the gradual-onset continuous performance task (gradCPT) [38] to build a connectome-based model (see Box 2) that predicted an individual's overall attention task performance from whole-brain functional connectivity patterns. Results suggested that distributed patterns of functional connectivity predicted unseen individuals' performance scores. The model generalized to predict attention task performance from fMRI data collected during rest, demonstrating that task-free functional connectivity alone can predict sustained attentional abilities. Furthermore, the model, defined using data from a non-clinical population of young adults, generalized to resting-state data from an independent sample of children and adolescents to predict symptoms of attention deficit hyperactivity disorder (ADHD). This finding suggests that functional brain organization contains information about a person's general ability to focus even when attention is not actively taxed.

Box 2 Functional connectivity-based predictive modeling.

Connectome-based predictive modeling is an approach that predicts an outcome measure from an unseen individual from their pattern of functional brain connectivity (see Ref. [93] for methodological detail and [94] for 'ten simple rules' for practical implementation). Functional connectivity reflects statistical dependence (in fMRI, typically correlation) between the two brain regions' blood oxygen level-dependent (BOLD) signal time courses. When data from an entire scan or scan session is used to generate a single connectivity matrix for each individual, the resulting connectivity pattern is referred to as static or time-averaged connectivity. A person's whole-brain pattern of static functional connectivity is sometimes called their 'functional connectome' or 'functional connectivity fingerprint'.

When performing predictive modeling, it is important that the data used for training and testing are independent. For internal validation, the train-and-test separation can be conducted iteratively using cross-validation. For example, $1/k$ of participants' brain-behavior pairs can be held out for test while the rest of the participants' data can be used to train the model (e.g., k-fold cross-validation). On the other hand, when an independent dataset (usually collected from a different site with different stimulus and analysis pipelines) is available for external validation, every participant's data in one sample is used for model training, and the other sample for model testing. External validation is recommended whenever possible.

After training and testing data are separated, the first step of connectome-based predictive modeling is typically feature selection. During feature selection, functional connections related to the behavioral measure of interest (for example, those significantly correlated with training participants' behavioral scores) are retained for model building. In some cases, the feature set can be constrained with data reduction techniques such as principal component analysis before feature selection.

Model building can be accomplished with different approaches including linear, partial least squares, or support vector regression [79,95]. During model building, an algorithm of choice is applied to map training participants' behavioral scores (dependent variables) to their functional connections (independent variables). The trained model is then applied to the test set, meaning that unseen individual's brain features are input into the model to predict their behavior.

Predictive model performance can be measured in multiple ways, including mean squared error, prediction R^2, and Spearman or Pearson correlation between observed and the predicted behavioral measures [1,4,94]. Successful prediction suggests that functional connectivity patterns generalize beyond the training set to predict behavior.

Complementary work suggests that individual differences in widespread functional connectivity patterns, observed during task performance and rest, predict individual differences in sustained attention, including ADHD diagnoses and continuous performance task performance in children [2] and stop-signal task performance in adolescents [3]. These results suggest that an individual's static functional connectome may serve as a robust neuromarker of sustained attention, a component of attention critical in nearly every psychological task and everyday activity.

Predicting within-individual changes in attentional state

Although evidence suggests that functional connectivity patterns predict overall cognitive and attentional abilities, we know from our everyday experiences that our mental states are constantly changing. Sustained attention, in particular, dynamically fluctuates over time. Despite our best attempts to maintain an optimal level of focus, we experience lapses of attention due to factors including distraction, mind wandering, fatigue or boredom. During attention tasks, lapses can be characterized with behavioral measures including accuracy, response time, and response time variability (see Box 3).

The crux of predictive cognitive neuroscience now lies in whether brain signatures can predict such evolving internal states [39,40]. Given that static functional connectivity fingerprints predict individuals' overall sustained attention function, do changes in these patterns also capture changing attentional states? For example, does a neural signature of sustained attention distinguish periods when a person is optimally focused on a task versus mind wandering or distracted? Emerging evidence suggests that dynamic, or time-resolved, functional connectivity may be a more sensitive marker of individual differences than time-averaged functional connectivity ([41–43] but see Ref. [44]). In addition, preliminary evidence also suggests that dynamic functional connectivity may be a more sensitive marker of time-varying cognitive and attentional states than multivoxel patterns of blood oxygen level-dependent (BOLD) activity [45].

Although characterizing ongoing thoughts and internal states with ongoing brain connectivity changes is intuitively appealing, there is unresolved debate about whether functional connectivity dynamics capture

Box 3 Behavioral markers of sustained attentional abilities and states.

Researchers have characterized an individual's ability to maintain focus, as well as changes in their attentional states over time, with self-report scales [96,97], intermittent thought probes [98,99], physiological recordings [100], and behavioral task performance [38,101,102]. The most commonly used sustained attention task is the continuous performance task (CPT). CPTs require participants to respond to rare targets in a constant stream of stimuli (X-CPT) or respond to all stimuli except the rare target (not-X CPT). In some CPT variants, participants respond to targets with an alternative button press rather than a withheld response. Stimulus presentation is typically rapid, with a new stimulus appearing every approximately 1 s, and task duration ranges from minutes to hours.

Overall sustained attention function can be operationalized as mean task accuracy or sensitivity (hit rate relative to false alarm rate). Changes in attentional state and lapses can be indexed with trial-to-trial measures of accuracy and response time (RT). In many CPTs, slower and/or less variable RTs indicate more optimal task focus whereas faster and more erratic response times indicate less optimal focus [103,104]. Mid-task mind-wandering probes can help distinguish arousal states (which reflect a person's available attentional resources) from sustained attentional states (which reflect both the available resources and how they are allocated) [20].

meaningful variability of cognition. Concerns arise from evidence that temporal variance is largely a result of sampling variability and head motion ([11,12], but see Refs. [43,46–48] for work on approaches to mitigate these problems). Furthermore, Gratton *et al.* [10••] showed that task-related variance in functional network connectivity is small compared to person-related variance, suggesting that connectome-based modeling may be less suited to predict state-level changes within an individual.

A large body of work, on the other hand, shows that functional connectivity patterns are sensitive to different task conditions as well as ongoing cognitive state differences within a task. For example, functional connectivity observed during windows as short as 22.5 s predicts which of several cognitive tasks an individual is performing [18]. Functional brain networks reconfigure adaptively into functionally segregated and integrated states with cognitive task demands (e.g., blocks of high and low working memory load in the *n*-back task) [15] which has consequences for behavioral task performance [49,50] and learning [51]. Recent work has even suggested that functional network and node boundaries themselves change with task states [14••]. These results demonstrate that functional brain networks flexibly reconfigure with changes in cognition and attention, suggesting that time-varying functional connectivity may predict ongoing internal states.

Predicting attention changes during task performance

Supporting the idea that functional connectivity dynamics in part reflect behavioral performance dynamics, Rosenberg *et al.* [17••] asked whether the same functional connectivity model that predicted individual differences in sustained attention also predicts changes in attentional states within an individual. This study used the validated signature of sustained attention from previous work [4] to predict within-individual variance in behavioral performance across 3-min blocks of the gradCPT. Not only did task-block functional connectivity predict task-block performance, but functional connectivity measured during rest breaks in between the blocks predicted performance of the neighboring task blocks. In addition, the model predicted week-to-week changes in the gradCPT performance of a single participant scanned 30 times over the course of 10 months [14••]. Importantly given the influence of head motion on functional connectivity, control analyses demonstrated that successful predictions were not driven by motion. Together these results demonstrate that the model of sustained attention tailored to predict individual differences also generalizes to predict periods of betters and worse sustained attention task performance within an individual.

Evidence suggests that a group-based model of sustained attention generalizes to capture within-subject differences in attention. It remains an open question, however, whether predictive models can be personalized to each individual. For example, can we build models using leave-one-trial-out, block-out, run-out, or session-out cross-validation to predict attention fluctuations in single individuals? Would such person-specific models capture state-level variance in attentional states better than group-based models? To begin addressing this question, Rosenberg *et al.* [17••] performed a complementary analysis of the same 30-session dataset using leave-one-session-out cross-validation. Models were trained using data from 29 sessions and tested on data from the held-out session. Intriguingly, this within-subject model significantly predicted left-out sessions' gradCPT performance but did not outperform the original group-based model. However, because this result is based on data from a single person, future work with densely sampled data from multiple individuals is needed to determine whether tailoring person-specific models to individual participants improves attention predictions.

Predicting attention changes in naturalistic contexts

Previous work suggests that functional connectivity dynamics capture changes in cognitive and attentional states during task performance. However, two primary questions remain. First, to what degree are connectome-based predictive models sensitive to moment-to-moment state changes that are not explicitly demarcated with external cues such as distinct task conditions and block or run breaks? Second, to what degree do connectome-based models of attention generalize to predict attentional state in ecologically valid contexts—that is, outside of traditional psychological tasks? Jangraw *et al.* [52] asked participants to read transcripts of Greek history lectures during fMRI and found that the connectome-based

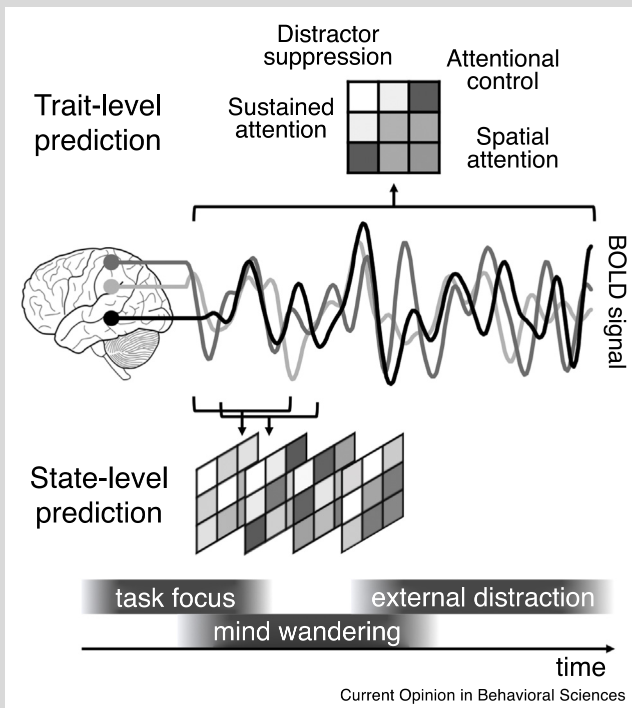
Box 4 Time-resolved predictive modeling of ongoing attention and cognition.

Dynamic predictive modeling, introduced by Song *et al.* [45], aims to predict evolving internal states from time-varying brain patterns. Models require dynamic measures of behavioral or physiological data as the predicted variables, time-aligned with dynamic functional connectivity patterns from multiple individuals (Figure B1). Dynamic functional connectivity, also known as time-resolved or time-varying functional connectivity, is commonly measured with sliding window analysis [105]. A single functional connectivity matrix is extracted by the statistical dependence of the time-courses within a certain length of temporal window (usually ranging from 30s to 60s). The window is slid across time, and connectivity matrices are repeatedly extracted at each window, throughout the scan duration.

As with static, or time-averaged, connectome-based predictive modeling (Box 2), data for training and testing are separated during feature selection and model building. Input data are all training participants' brain-behavior measures calculated at every time step. The time-courses of all functional connections and behavioral metrics are normalized across time within each feature. Importantly, normalization is not performed across features. This maintains within-feature temporal variance while removing across-individual and across-feature variance. The brain patterns and behavioral value corresponding to every time point (equivalent to repetition time [TR] in fMRI) from all training participants are treated as independent observations during model training. During model testing, the model is applied to held-out individuals' brain data observed at every time point to predict their behavioral time-course from their dynamic brain connectivity.

Because the outcome measure of interest is whether the model captures temporal variance in behavior rather than exact values, Pearson correlation between observed and predicted time-courses may be the most well-suited measure of model performance. Researchers can also consider complementary metrics including mean squared error and R^2 [59••].

Figure B1



Trait-level and state-level predictions of attention.
Static functional connectivity (top) is measured by computing the statistical dependence (e.g., correlation) between every pair of brain regions' BOLD signal time-courses. Static functional connectivity patterns can be used to predict different aspects of attention (Box 2), including sustained attention [2–4], distractor suppression [7], attentional control [5], or spatial attention. Dynamic functional connectivity, most commonly measured with sliding window analysis (bottom), may be used to predict attention fluctuations indexed with time-aligned behavioral or physiological data.

signature of sustained attention during reading predicted performance on a post-scan comprehension test. This work demonstrates the possibility that the functional connectivity signature of sustained attention, when measured during a naturalistic task such as reading, reflects aspects of attentional state consequential for comprehension. However, it remains unclear whether the same model predicts time-varying attentional states, and whether a model defined to predict performance on a visual continuous performance task will generalize to explain variance in real-world sustained attention fluctuations.

To characterize fluctuating brain states in the absence of explicit task switches, a growing number of neuroimaging experiments use 'naturalistic stimuli' such as movies and audio-narrated stories [53–55]. Studies have observed synchronized functional connectivity fluctuations as participants watched the same movies or listened to the same stories, and showed that these fluctuations are reliably coupled to the narrative elements of the story [45,56,57,58•]. Betzel *et al.* [57], for example, showed that moments when functional connectivity dynamics are more synchronized across individuals correspond to highly integrated brain states, and identified statistical associations between functional connection synchrony and the visual and semantic features of the movie. Van der Meer *et al.* [58•] compared resting-state to movie-viewing data and demonstrated that functional brain network dynamics are not only richer but more synchronous across people and across an individual's repeated sessions during movie viewing compared to rest. The occurrences of and transitions between large-scale brain states were explained by movie annotations and participants' physiological indices including heart rate and pupil diameter, and correlated with individual differences in subjective engagement to the movies. Furthermore, Song *et al.* [45] characterized transitions between functionally integrated and segregated brain states as participants actively tried to comprehend temporally scrambled movies, and showed that an active understanding occurred during moments when participants encountered events that are causally important in the narratives. Dynamic connectome-based predictive modeling (see Box 4) revealed that models based on time-varying functional connectivity generalized across movie stimuli to predict unseen individual's evolving degrees of comprehension.

Using the same dynamic connectome-based predictive modeling approach, recent work directly probed changes in attentional engagement during narratives [59••]. In behavioral studies, participants reported how engaging they found a television episode [60] or an audio-narrated story [61] by continuously adjusting a scale bar. Functional MRI analyses revealed that time-varying functional connectivity predicted not only fluctuating engagement, but also post-scan recall fidelity of narrative events, highlighting the network-level prediction of real-world attention and memory. The predictive models generalized across unseen individuals and independent datasets. Furthermore, multivariate patterns of connectivity in the sustained attention network previously defined by Rosenberg *et al.* [4] predicted changes in attentional engagement during the television episode. The sustained attention network overlapped with the network explicitly trained to predict narrative engagement, suggesting that distinct networks with shared subcomponents predict attention in controlled and naturalistic contexts. Together, this work illustrates how generalizing connectome-based models to within-individual state changes in naturalistic contexts can elucidate neural signatures of sustained attention.

Predicting attention changes during rest

In addition to interest in predicting attention changes as participants engage with external tasks and stimuli, there is significant interest in relating time-varying functional connectivity to internal states during rest—that is, in the absence of an explicit controlled or naturalistic task. An apparent difficulty lies in the fact that the optimal measure of a person's internal state during a resting-state scan, let alone dynamic changes in this state, is unclear. Nevertheless, the ability to predict evolving attentional states in the absence of an explicit psychological task could be useful for both theoretical and practical reasons. Prediction during rest could inform theories about why we can use resting-state data to predict individual differences in attention (e.g., by asking whether predictions are driven by, or independent from, attentional state dynamics during rest), contribute to understanding of the system-level neural reconfigurations that accompany spontaneous thoughts [62], and help reduce noise in data during preprocessing by identifying periods of low compliance for exclusion.

Initial progress has been made toward this goal [46,63•]. Gonzalez-Castillo *et al.* [63•] demonstrated that distinct cognitive states, annotated with Neurosynth's cognitive state 'topics', can be decoded from functional connectivity dynamics during rest. However, although analyses were restricted to data that had the least head motion and sleepiness confounds, the authors note that there was large inter-subject variability in brain state dynamics and that distinct periods of cognitive states during rest were poorly captured by dynamic functional connectivity compared to task.

To overcome these limitations, studies may consider collecting concurrent behavioral (e.g., experience sampling with intermittent thought probes) and physiological (e.g., skin conductance, pupillometry) measures during resting-state scans to characterize ongoing internal states. Highly sampled, concurrent measurements can provide rich dimensional indicators of participant's endogenous experiences during scans. For example, Kucyi *et al.* [64] used a finger tapping task during scans without any external stimulus, in which participants were instructed to tap their finger every 600 ms throughout the scan. The study used behavioral response variability (collected at every second of the scans) as a proxy for fluctuating attentional states. Furthermore, recent advances in reducing high-dimensional brain states into low-dimensional [63•,65,66] connectivity gradients, which retain biologically meaningful organizational principles [67], may enhance the interpretability and predictive performance of models that characterize ongoing attention and cognition during rest [68,69].

One way to achieve 'cognitive decoding' from resting-state data could be to build robust and generalizable predictive models of ongoing cognition from task fMRI data paired with simultaneous, highly sampled behavioral data. These models could be tested using naturalistic neuroimaging data, in which brain activity and connectivity are simultaneously driven by the continuous stream of external stimuli and internal state fluctuations. Models that successfully generalize could then be applied to resting-state data and validated with measures of attentional state such as infrequent thought probes or eye-tracking measures. We will discuss theoretical benefits and practical ways of achieving attentional state predictions from task, naturalistic, and rest data in the following section.

Looking ahead: disentangling state-like from trait-like aspects of functional connectivity

Characterizing the network predictors of different aspects of attention and changes in attentional processes over time can help delineate the independent components of attention [70], elucidate their interactions with cognitive processes such as comprehension and memory [52,59••], provide insight into their associated functional brain architecture, and inform the ways in which these architectures change to modulate internal states. In this review, we introduced work on connectome-based models that predict individual differences in sustained attention, which have generalized to predict different measures of the ability to maintain focus (including task performance and ADHD symptoms) in multiple datasets collected by independent research groups. We have also reviewed complementary work using time-varying brain connectivity to predict evolving attentional and cognitive states during controlled psychological tasks, naturalistic movie viewing and story listening, and rest.

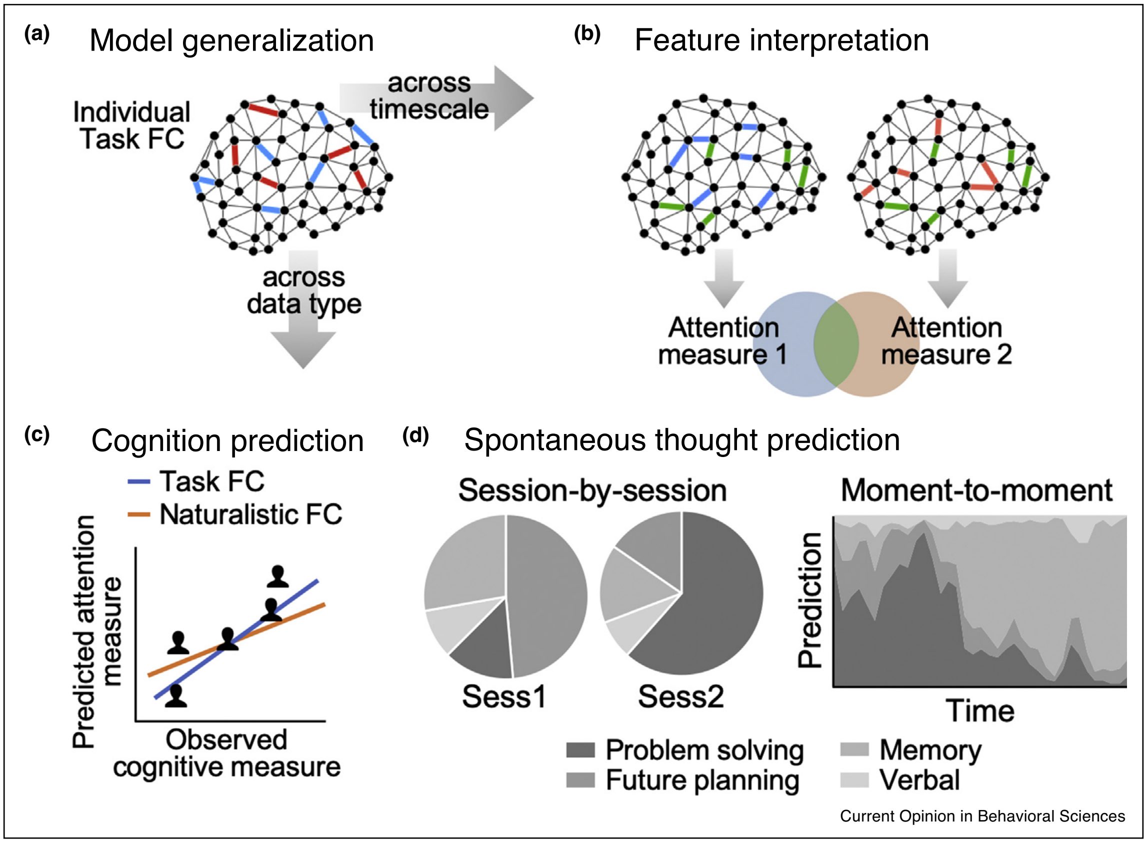
Despite significant progress predicting both inter-individual and intra-individual differences in sustained attention, a number of open questions remain. What proportion of variance in static functional connectivity patterns is explained by inter-individual versus intra-individual variance? Does this ratio vary as a function of cognitive state and scan type? To what degree does time-varying functional connectivity reflect cognitively meaningful brain states? Do attentional state fluctuations drive connectivity dynamics that would, without sufficiently sensitive behavioral or physiological metrics to validate them, otherwise be characterized as noise? We suggest that predictive modeling based on multi-session neuroimaging with highly sampled behavioral measures, or deep imaging, can help address these questions. Collection and analysis of densely sampled, multi-session data from participants engaged in a variety of experimental paradigms—ranging from controlled, semi-controlled, naturalistic tasks and rest—will allow researchers to characterize state-level variance on top of trait-level variance in functional connectivity. Together with predictive modeling on multiple timescales (Figure 1), work can ask whether an individual's moment-to-moment changes in functional connectivity, independent of their static functional connectivity 'fingerprint', reflect time-varying attentional, cognitive, and/or affective states during controlled and naturalistic tasks. Validated models can subsequently be applied to characterize ongoing internal states during rest, as participants experience endogenous fluctuations of attention. Behavioral sampling during or after resting-state scans will be useful for validating model performance.

Figure 2 outlines outstanding questions that can be addressed with predictive modeling across time and contexts. First, testing model generalization across time and contexts can provide new insight into the distinct or overlapping functional architecture of different attention components (Figure 2a). For example, testing the degree to which a model trained to predict individual differences in sustained attention during task performance predicts attentional engagement and other types of attention, such as spatial attention and attentional control, during naturalistic viewing or spontaneous thoughts (i.e., generalization across contexts) can delineate the taxonomy of attention and its neural substrates. Furthermore, testing the degree to which a static connectome-based model of sustained attention predicts dynamically changing attention and vice versa (i.e., generalization across time) can tell us how an individual's trait-like functional connectivity pattern is dynamically modulated to represent fluctuating attentional states.

Figure 2b illustrates ways in which deep imaging can improve the interpretability of brain features in predictive models, a challenging problem in machine learning especially when features are correlated with each other [71]. First, imagine a hypothetical dataset of multiple individuals each performing two sessions of the same sustained attention task. The test-retest reliability of predictive model feature weights could be assessed by comparing the feature maps from models built to predict performance in the first and second sessions separately. Second, imagine that participants had instead performed a sustained attention task in session one and watched a movie in session two. Comparing models that predict sustained attention task performance from session one data and narrative engagement from session two data—and asking whether the degree of overlap in predictive networks exceeds what would be expected by chance alone—can help narrow down a set of features related to both attentional processes or unique to each context. Thus, considering the overlap between functional networks predicting the same and different measures of attention can facilitate feature interpretation.

Third, datasets that include multiple behavioral measures can inform relationships between attention and other cognitive processes, including memory, learning, and

Figure 2



Outstanding questions in predictive modeling research.
We envision four main questions that can be addressed with multi-session neuroimaging and predictive modeling. **(a)** Do predictive models, defined using an individual's static functional connectivity 'fingerprint' observed in one task state, generalize to predict attention characterized at finer timescales and with different data types? In the schematic brain, colored lines show the anatomy of a hypothetical predictive model, indicating functional connections that are positively (red) or negatively (blue) correlated with individual differences in task performance. **(b)** How consistent or distinct are networks that predict attention? One way to ask this question is to assess the overlap of independently defined models. The colored lines indicate functional connections that predict different measures of attention in different contexts. Green connections predict both behavioral scores, whereas blue and orange connections are unique to each model. **(c)** Do models trained to predict aspects of attention generalize to predict other cognitive processes, such as memory, learning, or decision making? The figure illustrates a hypothetical relationship between an observed cognitive measure and an attention measure predicted from task-based and naturalistic connectivity. **(d)** Do models trained to predict behavioral measures of attentional state during tasks and naturalistic paradigms generalize to predict spontaneous thoughts during rest? The figure on the left illustrates a hypothetical set of model predictions from two sessions of static resting-state connectivity, corresponding to estimated probabilities that an individual is engaging in certain patterns of thought. In this example, the model predicts that the individual is likely to be planning for the future during the first rest session, but in a cognitive state related to problem solving during the second rest session. The figure on the right illustrates moment-to-moment changes in these probabilities, decoded from time-varying resting-state functional connectivity. In this example, the participant's evolving functional connectivity patterns suggest that they are likely to be engaged in problem solving during the initial part of the scan but memory towards the end of the scan.

decision making. Figure 2c illustrates an example where connectome-based models of attention are independently defined from controlled and naturalistic task fMRI data. Studies can ask whether these models not only predict attention but individuals' cognitive abilities as well. For example, a study can ask if an individual's sustained attention network strength during a memory task is predictive of their memory performance. Similarly, integrating multi-voxel pattern-based decoding analysis of perceptual and semantic features of visual items or scenes, studies can apply dynamic connectome-based modeling to predict moment-to-moment attentional state and ask how attention dynamically modulates perceptual or semantic representations of the brain [72,73].

Lastly, Figure 2d prospects ways in which validated models can be applied to predict session-by-session or moment-to-moment changes in spontaneous thought content during rest. After characterizing network-level brain states representative of cognitive states (e.g., problem solving, future planning, memory, or verbalizing) with task and naturalistic paradigms, studies can ask whether differences in resting-state functional connectivity are explained by differences in cognitive or attentional abilities and states.

Predictive modeling in psychological research

The utility of brain-based predictive modeling has been emphasized in translational research [71,74], for which the goal is to predict health-related outcomes. However, predictive modeling also has value for basic psychological research for which the overarching goal is to understand mental processes and behavior. Complementing explanatory models that characterize statistical associations between brain features and behavioral measures, predictive models forecast outcomes from unseen brain data and can be used to build and test theories of mental processes [75,76]. In this review, we introduced ways in which predictive models can be used to uncover the behavioral relevance of functional brain networks. With highly sampled behavioral measures assessed in diverse contexts, predictive models can untangle components of attention based on the underlying features of the brain that are involved [77]. They can also help address important questions about the test-retest reliability [78,79] and generalizability of neuroimaging findings [80].

Conclusion

Significant progress has been made toward building models that predict aspects of attention from static functional connectivity. Although work suggests that more variance in functional connectivity patterns is explained by individuals than states, a burgeoning literature provides evidence that connectivity dynamics do in part reflect attentional and cognitive state dynamics during controlled and naturalistic tasks and rest. Looking ahead, highly sampled fMRI and behavioral data in a wide range of cognitive states and task contexts will help elucidate the behavioral relevance of functional network dynamics across time scales and facilitate the development of a suite of brain-based predictive models of human attention and cognition.

Conflict of interest statement

Nothing declared.

Acknowledgements

This work was supported by the University of Chicago Social Sciences Division and a Neubauer Family Foundation Distinguished Scholar Doctoral Fellowship from the University of Chicago to H.S.

References and recommended reading

Papers of particular interest, published within the period of review, have been highlighted as:

- • of special interest
- •• of outstanding interest

1. Finn ES, Shen X, Scheinost D, Rosenberg MD, Huang J, Chun MM, Papademetris X, Constable RT: **Functional connectome fingerprinting: identifying individuals using patterns of brain connectivity**. *Nat Neurosci* 2015, **18**:1664-1671.

2. Kessler D, Angstadt M, Sripada C: **Growth charting of brain connectivity networks and the identification of attention impairment in youth**. *JAMA Psychiatry* 2016, **73**:481-489.

3. O'Halloran L, Cao Z, Ruddy K, Jollans L, Albaugh MD, Aleni A, Potter AS, Vahey N, Banaschewski T, Hohmann S *et al.*: **Neural circuitry underlying sustained attention in healthy adolescents and in ADHD symptomatology**. *Neuroimage* 2018, **169**:395-406.

4. Rosenberg MD, Finn ES, Scheinost D, Papademetris X, Shen X, Constable RT, Chun MM: **A neuromarker of sustained attention from whole-brain functional connectivity**. *Nat Neurosci* 2016, **19**:165-171.

5. Fountain-Zaragoza S, Samimy S, Rosenberg MD, Prakash RS: **Connectome-based models predict attentional control in aging adults**. *Neuroimage* 2019, **186**:1-13.

6. Rosenberg MD, Hsu WT, Scheinost D, Constable RT, Chun MM: **Connectome-based models predict separable components of attention in novel individuals**. *J Cogn Neurosci* 2018, **30**:160-173.

7. Poole VN, Robinson ME, Singleton O, DeGutis J, Milberg WP, McGlinchey RE, Salat DH, Esterman M: **Intrinsic functional connectivity predicts individual differences in distractibility**. *Neuropsychologia* 2016, **86**:176-182.

8. Wu EXW, Liaw GJ, Goh RZ, Chia TTY, Chee AMJ, Obana T, Rosenberg MD, Yeo BTT, Asplund CL: **Overlapping attentional networks yield divergent behavioral predictions across tasks: neuromarkers for diffuse and focused attention?** *Neuroimage* 2020, **209**:116535.

9. Cole MW, Bassett DS, Power JD, Braver TS, Petersen SE: **Intrinsic and task-evoked network architectures of the human brain**. *Neuron* 2014, **83**:238-251.

10. •• Gratton C, Laumann TO, Nielsen AN, Greene DJ, Gordon EM, Gilmore AW, Nelson SM, Coalson RS, Snyder AZ, Schlaggar BL *et al.*: **Functional brain networks are dominated by stable group and individual factors, not cognitive or daily variation**. *Neuron* 2018, **98**:439-452.e5

Gratton *et al.* characterized differences in functional connectivity patterns across individuals, scan sessions, and task states in the Midnight Scan Club dataset [85], which includes approximately 10 hours of fMRI data collected from nine individuals across 10 days and five task states. They found that functional network organization was largely explained by shared group and person-specific factors. Session and task state explained substantially less variance in connectivity patterns.

11. Laumann TO, Snyder AZ, Mitra A, Gordon EM, Gratton C, Adeyemo B, Gilmore AW, Nelson SM, Berg JJ, Greene DJ *et al.*: **On the stability of BOLD fMRI correlations**. *Cereb Cortex* 2017, **27**:4719-4732.

12. Parkes L, Fulcher B, Yücel M, Fornito A: **An evaluation of the efficacy, reliability, and sensitivity of motion correction strategies for resting-state functional MRI**. *Neuroimage* 2018, **171**:415-436.

13. Noble S, Spann MN, Tokoglu F, Shen X, Constable RT, Scheinost D: **Influences on the test-retest reliability of functional connectivity MRI and its relationship with behavioral utility**. *Cereb Cortex* 2017, **27**:5415-5429.

14. •• Salehi M, Greene AS, Karbasi A, Shen X, Scheinost D, Constable RT: **There is no single functional atlas even for a single individual: functional parcel definitions change with task**. *Neuroimage* 2020, **208**:116366

Salehi *et al.* collected fMRI data as the same participant performed six cognitive tasks and rested in 30 separate scan sessions. Defining an individualized functional parcellation scheme using data from each task and rest run separately, they found that functional parcel boundaries differed between task conditions and remained consistent within condition. Furthermore, subtle variations in parcel size between runs from the same task condition predicted session-to-session changes in task performance.

15. Shine JM, Bissett PG, Bell PT, Koyejo O, Balsters JH, Gorgolewski KJ, Moodie CA, Poldrack RA: **The dynamics of functional brain networks: integrated network states during cognitive task performance**. *Neuron* 2016, **92**:544-554.

16. Rosenberg MD, Zhang S, Hsu WT, Scheinost D, Finn ES, Shen X, Constable RT, Li CSR, Chun MM: **Methylphenidate modulates**

functional network connectivity to enhance attention. *J Neurosci* 2016, **36**:9547-9557.

17. Rosenberg MD, Scheinost D, Greene AS, Avery EW, Kwon YH,
•• Finn ES, Ramani R, Qiu M, Todd Constable R, Chun MM: **Functional connectivity predicts changes in attention observed across minutes, days, and months**. *Proc Natl Acad Sci U S A* 2020, **117**:3797-3807

Rosenberg *et al.* asked whether a validated connectome-based model of overall sustained attention function [4] predicted changes in attention over time in five independent data sets. They found that the model captured changes in attention task performance observed across 3-min task blocks and separate scan sessions. Furthermore, the model was sensitive to attentional and cognitive state changes induced by pharmacological interventions, such that people showed functional connectivity signatures of worse sustained attention when given anesthetic agents. Together the results suggest that fluctuations in the same functional connections that predict overall sustained attention ability also reflect fluctuations in attentional state.

18. Gonzalez-Castillo J, Hoy CW, Handwerker DA, Robinson ME, Buchanan LC, Saad ZS, Bandettini PA: **Tracking ongoing cognition in individuals using brief, whole-brain functional connectivity patterns**. *Proc Natl Acad Sci U S A* 2015, **112**:8762-8767.

19. Kucyi A, Daitch A, Raccah O, Zhao B, Zhang C, Esterman M,
• Zeineh M, Halpern CH, Zhang K, Zhang J *et al.*: **Electrophysiological dynamics of antagonistic brain networks reflect attentional fluctuations**. *Nat Commun* 2020, **11**

Kucyi *et al.* related changes in functional network dynamics measured with intracranial electroencephalography to ongoing sustained attention task performance. They found that activity in regions of the default mode and dorsal attention networks showed greater lagged anticorrelation during periods of better attention task performance.

20. Esterman M, Rothlein D: **Models of sustained attention**. *Curr Opin Psychol* 2019, **29**:174-180.

21. Oken BS, Salinsky MC, Elsas SM: **Vigilance, alertness, or sustained attention: physiological basis and measurement**. *Clin Neurophysiol* 2006, **117**:1885-1901.

22. Rosenberg MD, Chun MM: **Network models of attention and working memory**. In *The Cognitive Neurosciences,* edn 6. Edited by Poeppel D, Mangun GR, Gazzaniga MS.MIT Press; 2020.

23. Dubois J, Adolphs R: **Building a science of individual differences from fMRI**. *Trends Cogn Sci* 2016, **20**:425-443.

24. Finn ES, Glerean E, Khojandi AY, Nielson D, Molfese PJ, Handwerker DA, Bandettini PA: **Idiosynchrony: from shared responses to individual differences during naturalistic neuroimaging**. *Neuroimage* 2020, **215**.

25. Seghier ML, Price CJ: **Interpreting and utilising intersubject variability in brain function**. *Trends Cogn Sci* 2018, **22**:517-530.

26. Seitzman BA, Gratton C, Laumann TO, Gordon EM, Adeyemo B, Dworetsky A, Kraus BT, Gilmore AW, Berg JJ, Ortega M *et al.*: **Trait-like variants in human functional brain networks**. *Proc Natl Acad Sci U S A* 2019, **116**:22851-22861.

27. Miranda-Dominguez O, Mills BD, Carpenter SD, Grant KA, Kroenke CD, Nigg JT, Fair DA: **Connectotyping: model based fingerprinting of the functional connectome**. *PLoS One* 2014, **9**: e111048.

28. Greene AS, Gao S, Scheinost D, Constable RT: **Task-induced brain state manipulation improves prediction of individual traits**. *Nat Commun* 2018, **9**:1-13.

29. Avery EW, Yoo K, Rosenberg MD, Greene AS, Gao S, Na DL, Scheinost D, Constable TR, Chun MM: **Distributed patterns of functional connectivity predict working memory performance in novel healthy and memory-impaired individuals**. *J Cogn Neurosci* 2019, **32**:241-255.

30. Hakim N, Awh E, Vogel EK, Rosenberg MD: **Predicting cognitive abilities across individuals using sparse EEG connectivity**. *bioRxiv* 2020 http://dx.doi.org/10.1101/2020.07.22.216705.

31. Yamashita M, Yoshihara Y, Hashimoto R, Yahata N, Ichikawa N, Sakai Y, Yamada T, Matsukawa N, Okada G, Tanaka SC *et al.*: **A prediction model of working memory across health and psychiatric disease using whole-brain functional connectivity**. *eLife* 2018, **7**.

32. Hsu WT, Rosenberg MD, Scheinost D, Constable RT, Chun MM: **Resting-state functional connectivity predicts neuroticism and extraversion in novel individuals**. *Soc Cogn Affect Neurosci* 2018, **13**:224-232.

33. Feng C, Yuan J, Geng H, Gu R, Zhou H, Wu X, Luo Y: **Individualized prediction of trait narcissism from whole-brain resting-state functional connectivity**. *Hum Brain Mapp* 2018, **39**:3701-3712.

34. Beaty RE, Kenett YN, Christensen AP, Rosenberg MD, Benedek M, Chen Q, Fink A, Qiu J, Kwapil TR, Kane MJ *et al.*: **Robust prediction of individual creative ability from brain functional connectivity**. *Proc Natl Acad Sci U S A* 2018, **115**:1087-1092.

35. Gao M, Wong CHY, Huang H, Shao R, Huang R, Chan CCH, Lee TMC: **Connectome-based models can predict processing speed in older adults**. *Neuroimage* 2020, **223**:117290.

36. Ju Y, Horien C, Chen W, Guo W, Lu X, Sun J, Dong Q, Liu B, Liu J, Yan D *et al.*: **Connectome-based models can predict early symptom improvement in major depressive disorder**. *J Affect Disord* 2020, **273**:442-452.

37. Lee JJ, Kim HJ, Čeko M, Park B, Lee SA, Park H, Roy M, Kim SG, Wager TD, Woo CW: **A neuroimaging biomarker for sustained experimental and clinical pain**. *Nat Med* 2021 http://dx.doi.org/10.1038/s41591-020-1142-7.

38. Esterman M, Noonan SK, Rosenberg M, Degutis J: **In the zone or zoning out? Tracking behavioral and neural fluctuations during sustained attention**. *Cereb Cortex* 2013, **23**:2712-2723.

39. Cohen JR: **The behavioral and cognitive relevance of time-varying, dynamic changes in functional connectivity**. *Neuroimage* 2018, **180**:515-525.

40. Kucyi A: **Just a thought: how mind-wandering is represented in dynamic brain connectivity**. *Neuroimage* 2018, **180**:505-514.

41. Liégeois R, Li J, Kong R, Orban C, Van De Ville D, Ge T, Sabuncu MR, Yeo BTT: **Resting brain dynamics at different timescales capture distinct aspects of human behavior**. *Nat Commun* 2019, **10**:1-9.

42. Rashid B, Arbabshirani MR, Damaraju E, Cetin MS, Miller R, Pearlson GD, Calhoun VD: **Classification of schizophrenia and bipolar patients using static and dynamic resting-state fMRI brain connectivity**. *Neuroimage* 2016, **134**:645-657.

43. Vidaurre D, Llera A, Smith SM, Woolrich MW: **Behavioural relevance of spontaneous, transient brain network interactions in fMRI**. *Neuroimage* 2021, **229**:117713.

44. Fong AHC, Yoo K, Rosenberg MD, Zhang S, Li CSR, Scheinost D, Constable RT, Chun MM: **Dynamic functional connectivity during task performance and rest predicts individual differences in attention across studies**. *Neuroimage* 2019, **188**:14-25.

45. Song H, Park B, Park H, Shim WM: **Cognitive and neural state dynamics of story comprehension**. *bioRxiv* 2020 http://dx.doi.org/10.1101/2020.07.10.194647.

46. Duda M, Koutra D, Sripada C: **Validating dynamicity in resting state fMRI with activation-informed temporal segmentation**. *bioRxiv* 2020 http://dx.doi.org/10.1101/2020.10.12.335976.

47. Preti MG, Bolton TAW, Van De Ville D: **The dynamic functional connectome: state-of-the-art and perspectives**. *Neuroimage* 2017, **160**:41-54.

48. Ciric R, Wolf DH, Power JD, Roalf DR, Baum GL, Ruparel K, Shinohara RT, Elliott MA, Eickhoff SB, Davatzikos C *et al.*: **Benchmarking of participant-level confound regression strategies for the control of motion artifact in studies of functional connectivity**. *Neuroimage* 2017, **154**:174-187.

49. Cohen JR, D'Esposito M: **The segregation and integration of distinct brain networks and their relationship to cognition**. *J Neurosci* 2016, **36**:12083-12094.

50. Keerativittayayut R, Aoki R, Sarabi MT, Jimura K, Nakahara K: **Large-scale network integration in the human brain tracks temporal fluctuations in memory encoding performance**. *eLife* 2018, **7**.

51. Finc K, Bonna K, He X, Lydon-Staley DM, Kühn S, Duch W, Bassett DS: **Dynamic reconfiguration of functional brain networks during working memory training**. *Nat Commun* 2020, **11**:1-15.

52. Jangraw DC, Gonzalez-Castillo J, Handwerker DA, Ghane M, Rosenberg MD, Panwar P, Bandettini PA: **A functional connectivity-based neuromarker of sustained attention generalizes to predict recall in a reading task**. *Neuroimage* 2018, **166**:99-109.

53. Hasson U, Malach R, Heeger DJ: **Reliability of cortical activity during natural stimulation**. *Trends Cogn Sci* 2010, **14**:40-48.

54. Lee H, Bellana B, Chen J: **What can narratives tell us about the neural bases of human memory?** *Curr Opin Behav Sci* 2020, **32**:111-119.

55. Sonkusare S, Breakspear M, Guo C: **Naturalistic stimuli in neuroscience: critically acclaimed**. *Trends Cogn Sci* 2019, **23**:699-714.

56. Simony E, Honey CJ, Chen J, Lositsky O, Yeshurun Y, Wiesel A, Hasson U: **Dynamic reconfiguration of the default mode network during narrative comprehension**. *Nat Commun* 2016, **7**:1-13.

57. Betzel RF, Byrge L, Esfahlani FZ, Kennedy DP: **Temporal fluctuations in the brain's modular architecture during movie-watching**. *Neuroimage* 2020, **213**:116687.

58. • van der Meer JN, Breakspear M, Chang LJ, Sonkusare S, Cocchi L: **Movie viewing elicits rich and reliable brain state dynamics**. *Nat Commun* 2020, **11**:1-14

Van der Meer *et al.* characterized dynamic occurrences and transitions of brain states during repeated fMRI sessions of movie-watching and rest. Brain state dynamics were synchronized across individuals and repetitions during movie-watching, but not rest. Movie-watching was characterized by the involvement of, and fast transitions between, multiple brain states, which were also related to fluctuations in heart rate and pupil diameter during scans, annotated movie contents, and subjective engagement in the movies.

59. •• Song H, Finn ES, Rosenberg MD: **Neural signatures of attentional engagement during narratives and its consequences for event memory**. *bioRxiv* 2020 http://dx.doi.org/10.1101/2020.08.26.266320

In behavioral studies, Song *et al.* showed that moment-to-moment changes in self-reported attentional engagement to a television episode and audio story were synchronous across individuals. Applying group-average engagement ratings to two independent fMRI datasets [60,61], Song *et al.* found that time-varying functional connectivity predicted fluctuating engagement and post-scan recall fidelity of narrative events. Furthermore, the validated sustained attention network [4] predicted engagement dynamics during a television episode. This study illustrates how generalizing predictive models across time and contexts can elucidate sustained attention function and its impact on memory.

60. Chen J, Leong YC, Honey CJ, Yong CH, Norman KA, Hasson U: **Shared memories reveal shared structure in neural activity across individuals**. *Nat Neurosci* 2017, **20**:115-125.

61. Finn ES, Corlett PR, Chen G, Bandettini PA, Constable RT: **Trait paranoia shapes inter-subject synchrony in brain activity during an ambiguous social narrative**. *Nat Commun* 2018, **9**.

62. Kucyi A, Tambini A, Sadaghiani S, Keilholz S, Cohen JR: **Spontaneous cognitive processes and the behavioral validation of time-varying brain connectivity**. *Netw Neurosci* 2018, **2**:397-417.

63. • Gonzalez-Castillo J, Caballero-Gaudes C, Topolski N, Handwerker DA, Pereira F, Bandettini PA: **Imaging the spontaneous flow of thought: distinct periods of cognition contribute to dynamic functional connectivity during rest**. *Neuroimage* 2019, **202**

Gonzalez-Castillo *et al.* applied data-driven clustering on the dynamic functional connectivity to segment and decode distinct moments of cognitive states during multiple tasks [18] and rest [91]. The study demonstrates that distinct periods of cognitive states can be decoded from resting-state fMRI in a low-dimensional manifold, based on reverse inference of Neurosynth cognitive topics.

64. Kucyi A, Hove MJ, Esterman M, Hutchison RM, Valera EM: **Dynamic brain network correlates of spontaneous fluctuations in attention**. *Cereb Cortex* 2017, **27**:1831-1840.

65. Vidaurre D, Smith SM, Woolrich MW: **Brain network dynamics are hierarchically organized in time**. *Proc Natl Acad Sci U S A* 2017, **114**:12827-12832.

66. Shine JM, Breakspear M, Bell PT, Ehgoetz Martens K, Shine R, Koyejo O, Sporns O, Poldrack RA: **Human cognition involves the dynamic integration of neural activity and neuromodulatory systems**. *Nat Neurosci* 2019, **22**:289-296.

67. Margulies DS, Ghosh SS, Goulas A, Falkiewicz M, Huntenburg JM, Langs G, Bezgin G, Eickhoff SB, Castellanos FX, Petrides M *et al.*: **Situating the default-mode network along a principal gradient of macroscale cortical organization**. *Proc Natl Acad Sci U S A* 2016, **113**:12574-12579.

68. Hong SJ, Xu T, Nikolaidis A, Smallwood J, Margulies DS, Bernhardt B, Vogelstein J, Milham MP: **Toward a connectivity gradient-based framework for reproducible biomarker discovery**. *Neuroimage* 2020, **223**:117322.

69. Turnbull A, Karapanagiotidis T, Wang HT, Bernhardt BC, Leech R, Margulies D, Schooler J, Jefferies E, Smallwood J: **Reductions in task positive neural systems occur with the passage of time and are associated with changes in ongoing thought**. *Sci Rep* 2020, **10**:1-10.

70. Rosenberg MD, Finn ES, Scheinost D, Constable RT, Chun MM: **Characterizing attention with predictive network models**. *Trends Cogn Sci* 2017, **21**:290-302.

71. Nielsen AN, Barch DM, Petersen SE, Schlaggar BL, Greene DJ: **Machine learning with neuroimaging: evaluating its applications in psychiatry**. *Biol Psychiatry Cogn Neurosci Neuroimaging* 2020, **5**:791-798.

72. Çukur T, Nishimoto S, Huth AG, Gallant JL: **Attention during natural vision warps semantic representation across the human brain**. *Nat Neurosci* 2013, **16**:763-770.

73. deBettencourt MT, Cohen JD, Lee RF, Norman KA, Turk-Browne NB: **Closed-loop training of attention with real-time brain imaging**. *Nat Neurosci* 2015, **18**:470-478.

74. Woo CW, Chang LJ, Lindquist MA, Wager TD: **Building better biomarkers: brain models in translational neuroimaging**. *Nat Neurosci* 2017, **20**:365-377.

75. Shmueli G: **To explain or to predict?** *Stat Sci* 2010, **25**:289-310.

76. Yarkoni T, Westfall J: **Choosing prediction over explanation in psychology: lessons from machine learning**. *Perspect Psychol Sci* 2017, **12**:1100-1122.

77. Fair DA: **The big reveal: precision mapping shines a gigantic floodlight on the cerebellum**. *Neuron* 2018, **100**:773-776.

78. Noble S, Scheinost D, Constable RT: **A decade of test-retest reliability of functional connectivity: a systematic review and meta-analysis**. *Neuroimage* 2019, **203**:116157.

79. Taxali A, Angstadt M, Rutherford S, Sripada C: **Boost in test-retest reliability in resting state fMRI with predictive modeling**. *Cereb Cortex* 2021:bhaa390 http://dx.doi.org/10.1093/cercor/bhaa390.

80. Rosenberg MD, Song H: **Predicting post-stroke aphasia from brain imaging**. *Nat Hum Behav* 2020 http://dx.doi.org/10.1038/s41562-020-0902-1.

81. Poldrack RA, Gorgolewski KJ: **Making big data open: data sharing in neuroimaging**. *Nat Neurosci* 2014, **17**:1510-1517.

82. Smith SM, Nichols TE: **Statistical challenges in "big data" human neuroimaging**. *Neuron* 2018, **97**:263-268.

83. Horien C, Noble S, Greene AS, Lee K, Barron DS, Gao S, Connor DO, Salehi M, Dadashkarimi J, Shen X: **A Hitchhiker's guide to working with large, open-source neuroimaging datasets**. *Nat Hum Behav* 2020 http://dx.doi.org/10.1038/s41562-020-01005-4.

84. Miller KL, Alfaro-Almagro F, Bangerter NK, Thomas DL, Yacoub E, Xu J, Bartsch AJ, Jbabdi S, Sotiropoulos SN, Andersson JLR *et al.*: **Multimodal population brain imaging in the UK Biobank prospective epidemiological study**. *Nat Neurosci* 2016, **19**:1523-1536.

85. Gordon E, Laumann T, Gilmore A, Newbold D, Greene D, Berg J, Ortega M, Hoyt-Drazen C, Gratton C, Sun H *et al.*: **Precision functional mapping of individual human brains**. *Neuron* 2017, **95**.

86. Barch DM, Burgess GC, Harms MP, Petersen SE, Schlaggar BL, Corbetta M, Glasser MF, Curtiss S, Dixit S, Feldt C *et al.*: **Function in the human connectome: task-fMRI and individual differences in behavior**. *Neuroimage* 2013, **80**:169-189.

87. Nastase SA, Liu Y-F, Hillman H, Zadbood A, Hasenfratz L, Keshavarzian N, Chen J, Honey CJ, Yeshurun Y, Regev M *et al.*: **Narratives: fMRI data for evaluating models of naturalistic language comprehension**. *bioRxiv* 2020 http://dx.doi.org/10.1101/2020.12.23.424091.

88. Hanke M, Baumgartner FJ, Ibe P, Kaule FR, Pollmann S, Speck O, Zinke W, Stadler J: **A high-resolution 7-Tesla fMRI dataset from complex natural stimulation with an audio movie**. *Sci Data* 2014, **1**:1-18.

89. Aliko S, Huang J, Gheorghiu F, Meliss S, Skipper JI: **A naturalistic neuroimaging database for understanding the brain using ecological stimuli**. *Sci Data* 2020, **7**:347.

90. Alexander LM, Escalera J, Ai L, Andreotti C, Febre K, Mangone A, Vega-Potler N, Langer N, Alexander A, Kovacs M *et al.*: **An open resource for transdiagnostic research in pediatric mental health and learning disorders**. *Sci Data* 2017, **4**:1-26.

91. Van Essen DC, Smith SM, Barch DM, Behrens TEJ, Yacoub E, Ugurbil K: **The WU-Minn human connectome project: an overview**. *Neuroimage* 2013, **80**:62-79.

92. Casey BJ, Cannonier T, Conley MI, Cohen AO, Barch DM, Heitzeg MM, Soules ME, Teslovich T, Dellarco DV, Garavan H *et al.*: **The Adolescent Brain Cognitive Development (ABCD) study: imaging acquisition across 21 sites**. *Dev Cogn Neurosci* 2018, **32**:43-54.

93. Shen X, Finn ES, Scheinost D, Rosenberg MD, Chun MM, Papademetris X, Constable RT: **Using connectome-based predictive modeling to predict individual behavior from brain connectivity**. *Nat Protoc* 2017, **12**:506-518.

94. Scheinost D, Noble S, Horien C, Greene AS, Lake EM, Salehi M, Gao S, Shen X, O'Connor D, Barron DS *et al.*: **Ten simple rules for predictive modeling of individual differences in neuroimaging**. *Neuroimage* 2019, **193**:35-45.

95. Yoo K, Rosenberg MD, Hsu WT, Zhang S, Li CSR, Scheinost D, Constable RT, Chun MM: **Connectome-based predictive modeling of attention: comparing different functional connectivity features and prediction methods across datasets**. *Neuroimage* 2018, **167**:11-22.

96. Broadbent DE, Broadbent MHP, Jones JL: **Performance correlates of self-reported cognitive failure and of obsessionality**. *Br J Clin Psychol* 1986, **25**:285-299.

97. Cheyne JA, Carriere JSA, Smilek D: **Absent-mindedness: lapses of conscious awareness and everyday cognitive failures**. *Conscious Cogn* 2006, **15**:578-592.

98. Smallwood J, Davies JB, Heim D, Finnigan F, Sudberry M, O'Connor R, Obonsawin M: **Subjective experience and the attentional lapse: task engagement and disengagement during sustained attention**. *Conscious Cogn* 2004, **13**:657-690.

99. Christoff K, Gordon AM, Smallwood J, Smith R, Schooler JW: **Experience sampling during fMRI reveals default network and executive system contributions to mind wandering**. *Proc Natl Acad Sci U S A* 2009, **106**:8719-8724.

100. Unsworth N, Robison MK, Miller AL: **Pupillary correlates of fluctuations in sustained attention**. *J Cogn Neurosci* 2018, **30**:1241-1253.

101. Robertson IH, Manly T, Andrade J, Baddeley BT, Yiend J: **"Oops!": performance correlates of everyday attentional failures in traumatic brain injured and normal subjects**. *Neuropsychologia* 1997, **35**:747-758.

102. Rosenberg M, Noonan S, DeGutis J, Esterman M: **Sustaining visual attention in the face of distraction: a novel gradual-onset continuous performance task**. *Atten Percept Psychophys* 2013, **75**:426-439.

103. Esterman M, Rosenberg MD, Noonan SK: **Intrinsic fluctuations in sustained attention and distractor processing**. *J Neurosci* 2014, **34**:1724-1730.

104. deBettencourt MT, Norman KA, Turk-Browne NB: **Forgetting from lapses of sustained attention**. *Psychon Bull Rev* 2018, **25**:605-611.

105. Allen EA, Damaraju E, Plis SM, Erhardt EB, Eichele T, Calhoun VD: **Tracking whole-brain connectivity dynamics in the resting state**. *Cereb Cortex* 2014, **24**:663-676.