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ANNUAL REVIEWS

Annual Review of Developmental Psychology

Developmental Cognitive Neuroscience in the Era of Networks and Big Data: Strengths, Weaknesses, Opportunities, and Threats

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Keywords

network neuroscience; development; functional connectivity; brain; cognition; strengths, weaknesses, opportunities, and threats; SWOT

Abstract

Developmental cognitive neuroscience is being pulled in new directions by network science and big data. Brain imaging [e.g., functional magnetic resonance imaging (fMRI), functional connectivity MRI], analytical advances (e.g., graph theory, machine learning), and access to large computing resources have empowered us to collect and process neurobehavioral data

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faster and in larger populations than ever before. The translational potential from these advances is unparalleled, as a better understanding of complex human brain functions is best grounded in the onset of these functions during human development. However, the maturation of developmental cognitive neuroscience has seen the emergence of new challenges and pitfalls, which have significantly slowed progress and need to be overcome to maintain momentum. In this review, we examine the state of developmental cognitive neuroscience in the era of networks and big data. In addition, we provide a discussion of the strengths, weaknesses, opportunities, and threats (SWOT) of the field to advance developmental cognitive neuroscience's scientific and translational potential.

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Contents

1. THE MISSION OF DEVELOPMENTAL COGNITIVE NEUROSCIENCE

It might be hard to believe, but the term cognitive neuroscience—born out of a late-night New York City taxi ride (Gazzaniga 2014)—is now 50 years old. The term is meant to describe the understanding of how specific characteristics of the physical brain support various aspects of the mind. The phrase eventually resulted in a scientific discipline that merged basic neuroscience with psychology. Over the last five decades, cognitive neuroscience has advanced in ways its founders may not ever have imagined.

The intersection of basic neuroscience and psychology has not always seemed natural given the vast range of experimental methods used and outcomes studied (e.g., from individual gene expression to human behavior). Traditional studies of psychological phenomena remained rather independent from our understanding of the physical brain. The merging of the previously parallel fields of psychology and neuroscience benefited greatly from the emergence of positron emission topography (PET) and functional magnetic resonance imaging (fMRI). These technologies, which

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capitalize on the intricate coupling between neuronal activity and changes in metabolism and regional blood flow, made cognitive neuroscience possible (Raichle 2009).

Despite the great promise of functional neuroimaging for linking brain physiology to behavior, its limitations are stark. The early cognitive neuroscience pioneers were keenly aware of these limitations and worked together to solve fundamental problems that now may seem routine. Two such breakthroughs were atlas registration and group averaging of PET data. The interindividual heterogeneity in structural and functional neuroanatomy and low signal-to-noise ratio (SNR) of functional PET initially made it difficult to draw general conclusions about brain function. In addition, improving SNR for PET with repeated sampling was not possible due to the radiation exposure. A psychiatrist working in the lab of Marcus Raichle in the mid-1980s, Eric Reimen, proposed averaging PET data across people via a standardized atlas. As Gazzaniga notes, "The results of this approach were unambiguous, and the landmark paper that followed (P. T. Fox et al. 1988) presented the first integrated approach for the design, execution, and interpretation of functional brain images" (Gazzaniga et al. 2019, p. 18). Nearly 30 years later, this approach to brain imaging remains dominant; however, as discussed in the sections below, cognitive neuroscience has now revisited this issue and is starting to embrace the interindividual heterogeneity within subjects to further advance our understanding of brain function.

In a similar multidisciplinary collaboration, Michael Posner, Gordon Shulman, Marcus Raichle, and Steven Petersen created carefully controlled psychological paradigms for neuroimaging studies, enabling them to link behaviors, cognitive processes, and brain activation patterns. They combined best practices in cognitive psychology and systems neuroscience with emerging methods in biophysics, engineering, and mathematics to decipher activity and isolate the functional neuroanatomy of specific brain processes during task performance (Petersen et al. 1988, Posner & Raichle 1998, Raichle 1998). These and similar early efforts created cognitive neuroscience and represented the mainstay approach to characterizing brain–behavior correspondence for decades (see **Figure 1**) (Raichle 2009). Functional neuroimaging soon expanded beyond the study of adult brains, aiming to associate maturational brain changes and cognitive abilities in children, thus creating developmental cognitive neuroscience (DCN) (Davidson et al. 2003) (discussed in more detail in Section 2.4).

Today, much of cognitive neuroscience and DCN has shifted away from the detailed dissection of psychological processes and corresponding brain activations toward characterizing correspondences between complex behavioral phenotypes and distributed brain networks, often utilizing

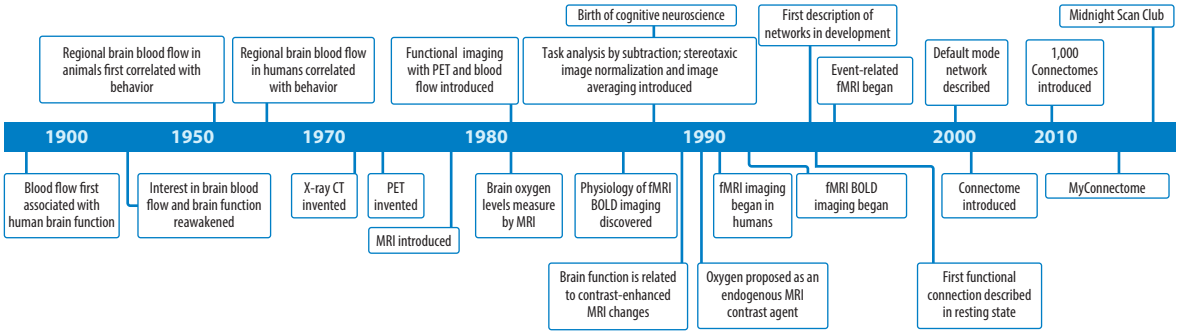

Figure 1

Timeline of developments in brain mapping and network neuroscience. Abbreviations: BOLD, blood oxygenation level–dependent; CT, computerized tomography; fMRI, functional magnetic resonance imaging; MRI, magnetic resonance imaging; PET, positron emission topography. Figure adapted with permission from Raichle (2009).

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emerging analytic strategies or those borrowed from other fields, such as machine learning. This change in cognitive neuroscience's scope has brought new concepts and new technologies that reinforce the field's promise to understand complex human brain function and translate its findings to beneficial applications. However, this shift also introduces new challenges and pitfalls that can slow progress.

The field of DCN in the era of big data continues to evolve as data are collected in broader populations at a faster rate than ever before. Network neuroscience and the view of the brain as consisting of multiple interconnected systems that support complex behavior have also advanced the field in new directions. However, the arrival of large-*N* data sets with thousands of participants and repeated sampling data sets with tens of hours of neuroimaging data per subject highlight that, in some situations, simply applying the cognitive neuroscience framework carried forward from the origins of our field to modern investigations is limiting advancement.

In this review, we examine the current state of the field in the era of brain networks and big data, focusing primarily on fMRI with an emphasis on functional connectivity (FC) MRI [as opposed to electroencephalogram (EEG) and other noninvasive functional modalities]. We highlight the history of advancements in the study of brain networks in development. We also highlight some of the pitfalls that the era of big data has unveiled. We end with a strengths, weaknesses, opportunities, and threats (SWOT) analysis of the field of cognitive neuroscience. The goal is to encourage discussion and movement in new directions that will put DCN on more solid footing moving forward.

2. THE RISE OF NETWORKS AND BIG DATA IN DEVELOPMENTAL COGNITIVE NEUROSCIENCE

The brain is a network across multiple levels of organization from molecules to systems. At the cellular level, nodes and links are formed by neurons and synapses, which are encompassed by the structural connectome. At the systems level, to which neuroimaging is sensitive, the cerebral cortex is organized into discrete functional areas that are connected structurally by white matter tracts and functionally by synchronized infraslow frequency activity (<0.1 Hz).

2.1. Earliest Brain Networks in Cognitive Neuroscience

The earliest proposals of large-scale brain networks within the context of cognitive neuroscience were multifold. Perhaps the most influential of these papers came from the early pioneers Michael Posner and Steven Petersen (Petersen & Posner 2012, Posner & Petersen 1990). In their 1990 review, which has now been cited over 9,000 times, the authors summarized the then-current state of knowledge regarding the functional underpinnings of attention using early PET imaging studies. Posner & Petersen proposed the conceptual separation of attentional processes related to alerting, selective attention shifting (orienting), and task control, which was primarily based on intricate psychological processes of alerting, visuospatial cueing, and conflict. They suggested that distinct sets of brain regions or networks preferentially carry signals related to each of these separable processes. Posner & Petersen (1990) also proposed several defining criteria for attentional control systems in the brain, including anatomical distinction from the sensory and motor systems and diverse regions of function. Further studies have described attentional networks with executive and organizational processes. It is hard to imagine that 30 years have passed since this initial work, but even more surprising is the work's vitality.

In 1998, Marcus Raichle and colleagues consistently observed a decrease in metabolic activity in distributed regions in the ventromedial prefrontal cortex and posterior cingulate cortex during a range of goal-directed behaviors (Raichle et al. 2001), which led to the proposal of a brain default mode and related default mode network. Several other dominant papers at the time revealed other

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potential systems with fMRI. For example, Corbetta & Shulman (2002) revealed their theory on the dorsal and ventral attention systems. In 2006, Dosenbach et al. hypothesized a core task control system (Dosenbach et al. 2006) that later became the cingulo-opercular network (Dosenbach et al. 2007, 2008) and salience systems (Seeley et al. 2007). These studies and many others laid the groundwork for what would rapidly evolve into network neuroscience with the introduction of FC MRI.

2.2. Resting State Functional Connectivity

The first functional connection was described in 1995 with the observation that spontaneous blood oxygenation level–dependent (BOLD) fluctuations in the infraslow frequency regime were correlated between the left and right primary motor cortex in the resting state (Biswal et al. 1995). This study was overshadowed by task-driven fMRI; however, it eventually served as a seminal report for subsequent studies to elucidate the functional network organization of the human brain.

FC was used to identify the so-called default mode network (DMN) (Greicius et al. 2003, Fransson 2005) noted above. Resting-state functional connectivity (RSFC) became more widely accepted in 2005 after Fox et al. (2005) showed that spontaneous fMRI signal fluctuations in the DMN were negatively correlated with fluctuations in a collection of brain regions commonly coactivated across tasks, an expansion on the findings by Greicius et al. (2003) and Fransson (2005). A key observation of the functional network approach was that cofluctuations during the resting state largely represent patterns observed during task activation (Cole et al. 2014).

Several follow-up FC reports highlight the presence of task control systems such as the frontoparietal network and cingulo-opercular networks (Dosenbach et al. 2008), salience system (Seeley et al. 2007), dorsal and ventral attention systems (Fox et al. 2006), and more (Power et al. 2011, Smith et al. 2009, Yeo et al. 2015).

2.3. The Connectome

The identification of functional networks with task fRMI and RSFC, two parallel but distinct techniques, initiated a shift away from region-of-interest approaches toward network approaches that characterized the whole connectome—a term introduced by Olaf Sporns and colleagues in 2005 (Sporns et al. 2005). Quantitative assessment of functional networks was made possible through the introduction of a branch of mathematics known as graph theory (Bullmore & Sporns 2009, Sporns et al. 2005). Graph theoretical applications to neuroscience (i.e., network neuroscience) provide a powerful way to understand brain functioning across regional, network, and whole-brain scales (Bullmore & Sporns 2009, Sporns et al. 2005). Graph theory and network neuroscience have provided a common framework for understanding and simplifying spatiotemporal aspects of whole-brain signals measured across conditions of rest and task. In a sign of its expansion in the neurosciences, in 2019, almost 15 years after its introduction into our vernacular, the term connectome was added to Webster's Dictionary.

2.4. Brain Networks in Developmental Cognitive Neuroscience

The human brain expands at an explosive rate during the first few years of life (Grayson & Fair 2017, Knickmeyer et al. 2008). This same time period is marked by rapid and widespread cortical synaptogenesis, followed by a protracted period of synapse elimination and cell loss that carries into adulthood (Huttenlocher 2009, Innocenti & Price 2005). The brain's major fiber pathways become consolidated through myelination, though their presence is largely established prenatally (Stiles & Jernigan 2010). Perhaps not surprisingly, brain network development parallels these changes.

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The first mentions of brain networks in the case of development occurred not too far removed from the first fMRI studies in adults by Kwong et al. (1992). It did not take long for investigators interested in developmental psychology to expand on these initial experiments in developmental samples. Such efforts were kicked off by B.J. Casey and colleagues in 1995 with their foundational work, *Activation of the Prefrontal Cortex in Children During a Nonspatial Working Memory Task with Functional MRI* (Casey et al. 1995). Shortly after, some of the original references for the brain as networks in developmental MRI samples came from early papers by Piven and colleagues (1997) on autism and Rapin & Katzman (1998) and Michael Posner et al. (1999) on attentional systems in development. Nonetheless, as in adult studies, this framework for understanding and characterizing the developing brain in cognitive neuroscience would not take hold for several years.

Resting-state networks measured with FC MRI are already present during infancy and potentially to some extent in utero (Thomason et al. 2013). Seed-based, component-based, and graph theory–based (i.e., community structure) approaches demonstrate the existence of robust, bilateral segregated networks for the somatomotor, primary auditory, primary visual, and extrastriate visual cortices (Fransson et al. 2007, Gao et al. 2015a, Smyser et al. 2010). These sensory and association networks undergo subtle refinements and strengthening over the first two years of life and by age two bear substantial resemblance to their adult counterparts (Alcauter et al. 2015; Damaraju et al. 2014; Gao et al. 2015a,b; Graham et al. 2015). New studies are now refining these trends in striking detail (Eyre et al. 2021) with the collective suggestion that sensory networks are formed at an age earlier than those networks involved in higher-level cognition (Gao et al. 2017). Such trends support findings that primary sensory regions are generally the first cortical areas to mature (Geng et al. 2017, Gilmore et al. 2012, Lyall et al. 2015, Scott et al. 2016). While there are less suggestive data in heteromodal association systems, as our methods for increasing signal and reducing noise improve (see Section 3.1), the same is likely to be found to be true for higher-order cognitive networks (De Asis-Cruz et al. 2015, Eggebrecht et al. 2017, van den Heuvel et al. 2015).

Many of the network changes seen during infancy reflect long-term trajectories that extend into childhood and adolescence. As with the infant literature, much of the research in children and adolescents has focused on the regions that define the adult DMN. Seed and component approaches have consistently found that connectivity between these areas (and indeed, connectivity within other cognitive resting state networks) continues to strengthen from early childhood throughout development, especially with respect to long-range anterior–posterior links (de Bie et al. 2012, Fair et al. 2008, Sato et al. 2014, Sherman et al. 2014, Supekar et al. 2010). Studies in children and adolescents highlight that brain networks are largely similar topographically to those seen in the adult (Fair et al. 2012, Gu et al. 2015, Marek et al. 2015, Power et al. 2010). While the spatial organization appears to be largely similar, investigators have consistently found that connectivity within and between networks continues to refine through young adulthood. Of note, most of our understanding of functional brain development in cognitive neuroscience comes from cross-sectional studies—a trend that is likely to change with the ongoing ABCD study following >10,000 9–10-year-olds over 10 years into young adulthood (Casey et al. 2018, Volkow et al. 2018) and the introduction of the Healthy Brain and Child Development (HBCD) Study, a longitudinal consortium study to evaluate brain development from the perinatal period to 10 years of age (Volkow et al. 2020).

2.5. Resting-State Functional Connectivity in Children and Adolescents

A reproducible finding within child and adolescent development had been an apparent shift from a local to a global organization with FC between local regions of interest decreasing as long-range FC increases until adulthood (Dosenbach et al. 2010, Fair et al. 2009, Kelly et al. 2009,

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Supekar et al. 2009). This FC pattern was due to the inhibition of nonspecific local spread and reinforcement of distal links, suggesting that cognition develops through modules and integration across networks (Bunge & Wright 2007, Fair et al. 2009, Uddin 2011, Uddin et al. 2011). The consistency of these findings is highlighted by the description of accurate predictions of a subject's age based on a single resting state scan (Dosenbach et al. 2010).

However, concerns about the influence of head motion artifacts have led to a reexamination of these broad brain development trends. In particular, it has been revealed that motion increases nonspecific local coupling and decreases long distance connectivity. More recent results of brain–behavior relationships utilizing functional fingerprinting have also been shown to be highly related to motion artifacts (Siegel et al. 2017). Nonetheless, recent evidence from one large study emphasizes that such person-specific networks mature in childhood and adolescence and are linked to individual differences in cognitive capacity. Cui et al. (2020) examined a large sample of youth (ages 8–23 years) who were part of the Philadelphia Neurodevelopmental Cohort (PNC). Using a recently developed machine learning technique and stringent quality control that identified a sample of PNC participants who had 27 min of low-motion fMRI data led to results that revealed there is marked interindividual heterogeneity in the spatial distribution of large-scale functional networks in children. This variability differed systematically across networks. Higher-order association networks—such as the frontoparietal control network, cingulo-opercular network, and DMN—were marked by high interindividual variability whereas sensorimotor networks showed only limited variability. Furthermore, children and adolescents who had a greater cortical representation of frontoparietal control networks showed better long-range coupling in ways that are similar to differences found between children and adults (Fair et al. 2012, Power et al. 2012, Satterthwaite et al. 2012, Yan et al. 2013). Developmental effects of this type (e.g., local versus distributed coupling) are substantially attenuated with motion correction, though still present to a more limited extent (Fair et al. 2012, Power et al. 2012, Satterthwaite et al. 2012). It is likely that functional network maturation follows more precise spatiotemporal trajectories than previously understood (Fair et al. 2012, Gu et al. 2015, Marek et al. 2015).

There is no question that the concepts of large-scale networks and their change over development has transformed DCN in recent years. Most functional studies (task fMRI, FC MRI, and even structural studies) are now conceptualized in the form of networks as opposed to assigning function to specific regions within the brain—a palpable shift within even the last decade.

2.6. The Rise of Big Data

As network neuroscience expanded our understanding of brain development, data sets were also increasing in sample size and/or the amount of data collected per subject.

2.6.1. Large sample sizes. The past decade has witnessed the emergence of a series of openly available, large-scale ($N > 1{,}000$) neuroimaging data resources spanning a range of populations and experimental designs. While many are the products of projects explicitly tasked with generating open data using either a single site [e.g., the Human Connectome Project (adult, $N = 1{,}200$), NKI-Rockland Sample (life span, $N = 1{,}500$)] or multisite design [e.g., the Alzheimer's Disease Neuroimaging Initiative (aging, $N = 1{,}600$), the National Institutes of Health (NIH) Adolescent Brain Cognitive Development (ABCD) Study (longitudinal developmental cohort, $N = 10{,}000$), the UK Biobank (early aging, $N = 100{,}000$)], others are the results of data sharing efforts that aggregate, organize, and share independently collected (i.e., heterogenous) data sets. Among the most notable of such efforts is the International Neuroimaging Data-Sharing Initiative and its grassroots consortia-based samples [e.g., the 1000 Functional Connectomes Project, ADHD-200,

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Autism Brain Imaging Data Exchange (ABIDE) I and II, Consortium for Reliability and Reproducibility (CoRR)].

These large-scale data resources have laid the foundations for the implementation of discovery science in the imaging community and studies of heterogeneity (e.g., developmental, neurobiological, clinical). As highlighted in a recent bibliometric analysis of shared data usage, these data sets have served to recruit scientists from a broader range of disciplines (Milham et al. 2018). These data resources also enabled the assessment and optimization of reproducibility across independent neuroimaging data sets (Zuo et al. 2019a) (see also Section 3.2).

With that said, large-*N* samples have revealed an inconvenient truth regarding population neuroimaging studies: Most effect sizes for brain–behavior relationships are smaller than previously expected (Button et al. 2013, Lefebvre et al. 2015, Marek et al. 2019, Smith & Nichols 2018). Study designs for correlating complex behavioral phenotypes outside the scanner up until recently have largely relied on the same, relatively small (median $N \approx 25$), sample sizes as traditional task fMRI studies from the origins of cognitive neuroscience. Task fMRI studies draw on repeated measures of specific in-scanner behaviors and their corresponding brain activations, enabling the generation of highly reproducible within-subject or group-averaged task activation maps. The realization that studies aiming to correlate brain metrics and complex cognitive phenotypes across individuals require much larger sample sizes than classical fMRI has impacted the interpretation of previous brain-wide association (BWA) study findings and how we should design and implement brain–behavior population studies in the future (Marek et al. 2020). Analyses of some of the largest neuroimaging data sets suggest that many true effects or outcomes for brain–behavior associations can be confirmed only with samples comprising thousands of participants (**Figure 2**). The larger effects reported by cross-sectional brain–behavior studies based on smaller samples are likely a reflection of publication bias that selects for the largest positive findings, inflating the apparent effect sizes (Button et al. 2013, Sabuncu & Konukoglu 2015, Smith & Nichols 2018, Walum et al. 2016). In the context of smaller-than-expected effect sizes and high population sampling variability, much larger BWA study samples are required to reduce statistical errors and to

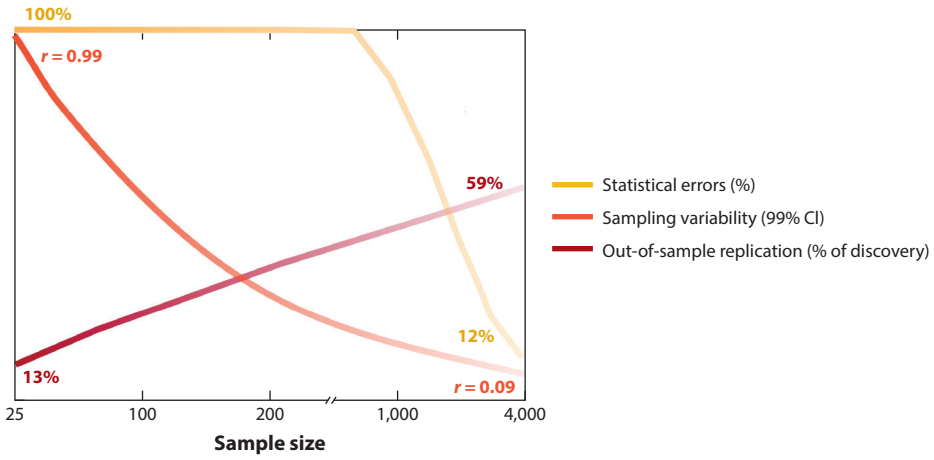

Figure 2

Trajectories of sampling variability (*orange*), statistical error rates (*yellow*), and reproducibility (*dark red*) as a function of sample size. Increasing brain-wide association study sample sizes into the thousands reduces sampling variability and statistical errors, which, in turn, promotes increased reproducibility of brain-wide associations. Abbreviation: CI, confidence interval. Figure adapted with permission from Marek et al. (2020).

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maximize replication (Abraham et al. 2017, Marek et al. 2020)—a truth the field cannot ignore. Importantly, not all effects are small (e.g., in development and aging), and while brain–behavior effect sizes are smaller than previously imagined for BWA studies compared with genome-wide association (GWA) studies, brain–behavior effects are relatively large (Marek et al. 2020).

2.6.2. Repeated sampling within subjects. Structural MRI (T1, T2) is extremely clinically valuable, because it can reveal the physical structure of individual brains with great detail on the basis of scans that are only a few minutes long. However, the SNR of functional neuroimaging data is low; thus, results obtained in individuals using standard quantities of per-subject data (5–30 min) cannot precisely characterize brain function. Hence, functional neuroimaging researchers have typically chosen to aggregate smaller amounts of data across many participants using methods initially developed for PET (see Section 1), resulting in a large majority of cognitive neuroscience focused on examining the group-average brain (although not always; e.g., functional localization studies).

The amount of fMRI data collected per subject in developmental studies is constrained by the amount of time children can remain still for an MRI scan, which ranges from 30–90 min. Typically 5–20 min of RSFC data are acquired in pediatric studies. While group averaging has revealed important global tendencies of functional brain organization, the lack of emphasis on studying individual brains means that little is known about interindividual variance in functional brain organization. Similarly, between-group studies of patients and controls have for the most part compared group means. Machine learning fMRI studies aimed at classifying individuals as patients or controls have mostly failed to provide deeper pathophysiological insights and have yet to enter into clinical use. Even the most advanced algorithms cannot overcome the fundamental SNR limitations of functional neuroimaging.

Hence, human functional neuroimaging has been in need of a paradigm shift that complements large, sufficiently powered group studies with a systematic characterization of functional brain organization in individual humans. Individual-specific functional neuroimaging is critical for determining to what degree differences in brain organization are behavior-related, epiphenomenal, genetically determined, shaped by the environment, disease-causing, or none of these. It also empowers the study of individuals with idiosyncratic brain lesions, rare disorders, or unusual cognitive skills, all of which will deepen our understanding of human brain function (Laumann et al. 2021).

The first step toward conceiving individual-specific functional neuroimaging was taken by Russ Poldrack, who collected functional neuroimaging data on himself twice a week for more than a year for his MyConnectome Project (Poldrack et al. 2015). The MyConnectome data revealed that (*a*) with sufficient data (many hours), reliable estimates of brain networks can be produced in a single individual; (*b*) features of Poldrack's network map closely corresponded with his task-driven fMRI activations; and, most notably, (*c*) Poldrack's individual brain networks were more detailed than group-average networks, in which small features are obscured by averaging across individuals (Gordon et al. 2017, Laumann et al. 2015). The MyConnectome data revealed that individual specificity could be achieved with extensive repeated sampling within individuals.

Inspired by the MyConnectome project and capitalizing on a 90% reduction in scanner fees after midnight, the Midnight Scan Club (MSC) collected high-fidelity individual-specific fMRI data sets in 10 individuals (5 h of RSFC and 15 h of task fMRI per subject) (Gordon et al. 2017). The MSC data showed that the group average is not a good representation of any one of the individual brains (Gordon et al. 2020, 2021; Gratton et al. 2018; Greene et al. 2020; Marek et al. 2018; Raut et al. 2020; Sylvester et al. 2020; Zheng et al. 2020). The MSC data enabled researchers to compare precise functional brain maps, each one based on five h of data, across individuals for

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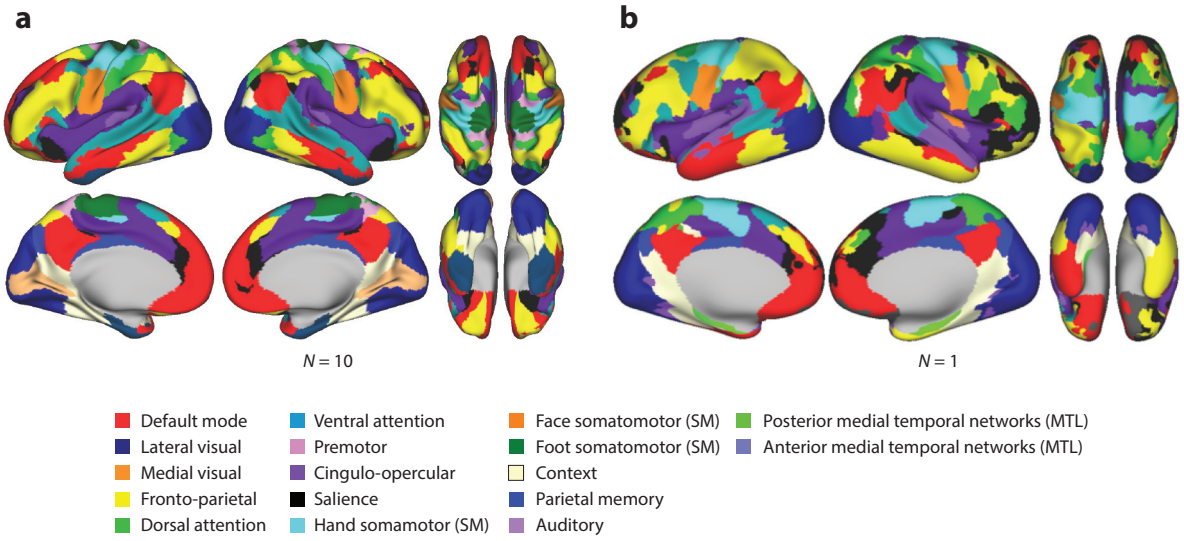

Figure 3

Notable differences in the individual brain versus the group average. (*a*) Group averaged ($N = 10$) and (*b*) individual brain topography ($N = 1$) Figure adapted with permission from Gordon et al. (2017).

the first time. While there were strong similarities across all individual brains, each one of the ten MSC participants had a clearly distinct functional brain map and was perfectly separable from each of the other study participants (**Figure 3**). The MyConnectome, MSC, and other similar high-fidelity data sets are openly available to the research community (Anderson et al. 2014, Duchesne et al. 2021, O'Connor et al. 2017, Weng & Zuo 2014).

Growing evidence from different samples, methods, and research groups emphasizes that large-scale functional networks differ significantly in their spatial distribution across individuals (Braga & Buckner 2017, Elliott et al. 2021, Gordon et al. 2017, Gratton et al. 2020, Lynch et al. 2020, Naselaris et al. 2021) Together, these results emphasize the relevance of personalized functional mapping techniques for understanding functional network development in youth and also suggest opportunities in clinical translation (see Section 3.1).

2.7. Conclusion

Network methods, large sample sizes (*N*), and repeated sampling (small *N*) studies (see **Figure 3**) have brought us to the following realizations: Individual networks are important, and group averaging is likely obscuring details and reducing effect sizes. Traditional population studies are going to require more data than previously recognized, both per subject and in terms of sample sizes (Feczko & Fair 2020). How one collects data and how much data to collect need to be driven by the specifics of the hypotheses being asked by the investigator. Repeated sampling within subjects and maximizing sample size carry distinct advantages depending on the scientific question at hand.

3. STRENGTHS, WEAKNESSES, THREATS, AND OPPORTUNITIES IN DEVELOPMENTAL COGNITIVE NEUROSCIENCE

The insights gained from recent big data studies in DCN have drastically changed the way we analyze data and how future studies will be designed. While such growing pains are typical for any scientific discipline, DCN is at a crossroads, and our future success is dependent on reflection

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and proper course correction. The level of cooperation and resources required for reproducible DCN demands a major paradigm shift. Study designs for BWA studies cannot simply borrow the study designs and analysis methods optimized for PET and task fMRI from 30 years ago. To be successful moving forward, we need a clear-eyed evaluation of the current state of DCN.

Therefore, this review concludes with an analysis of strengths, weaknesses, threats, and opportunities—a popular exercise to identify what an organization is doing well and what it needs to adjust for success. Progress of an enterprise requires consistent evaluation of internal factors that can advance (strengths) or halt (weaknesses) momentum as well as external environmental factors that can harm (threats) or be leveraged (opportunities) by an organization. Herein, we identify such key factors within the cognitive neuroscience community and place them in context within the current scientific landscape to reflect and initiate change moving forward.

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3.1. Strengths

As introduced in Section 2, the field of DCN has evolved to develop and incorporate numerous strengths that are critical to maintain and reinforce in order to advance toward the overarching mission of understanding the relationship between brain function and cognition.

3.1.1. Incorporation of advanced neuroimaging technologies. Over the last two decades, innovative perspectives, tools, and methods have been added to DCN. Novel approaches to data acquisition, such as multiband MRI technologies (Moeller et al. 2010) and analytical techniques in network neuroscience, as described in previous sections, have extended and refined previous findings in functional neuroimaging. DCN is also benefiting from the application of other broadening methods, such as multiecho extensions of multiband imaging, expansion of prospective motion correction techniques, and deep learning. For example, Keshavan et al. (2019) applied deep learning trained on a crowd-amplified data set from the Healthy Brain Network and demonstrated improved quality control of MRI analyses in studies of brain development (Keshavan et al. 2019).

3.1.2. Appreciation for heterogeneity in behavior, physiology, neuroanatomy, and developmental trajectories. It has been common to assume the homogeneity of developmentally or clinically defined populations when evaluating brain–behavior relationships. This heterogeneity problem is now widely recognized and highlights that any human mental health syndrome or outcome, from cognitive functions to clinical disorders, will not necessarily be caused by a single mechanism, but rather by different combinations of many mechanisms (Baller et al. 2021, Feczko et al. 2019, Feczko & Fair 2020, Kaczkurkin et al. 2020, Satterthwaite et al. 2020). A better understanding of such population variance is critically important for DCN. It is also a necessity for grouping individuals into more homogenous samples, thus reducing sampling variability in translational studies. Such phenomena may lead to dimensional relationships where a brain–behavior relationship that is unique to one homogeneous population is distinct from that of another group of individuals (Chabernaud et al. 2012).

3.1.3. Access to big data. As described in Section 2, collecting big data and providing access to it is actively encouraged by funding agencies and the scientific community, as exemplified by the growing list of government- and community-led efforts to do so, including BioBank (Littlejohns et al. 2020), the ABCD study (Feczko et al. 2021, Volkow et al. 2018), the Human Connectome Project (Van Essen et al. 2013), the All of Us research program (All of Us Res. Program Investig. 2019), the International Neuroimaging Data Sharing Initiative and its grassroots consortia [e.g., the 1000 Functional Connectomes Project (Biswal et al. 2010), the ADHD-200

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(ADHD-200 Consort. 2012), ABIDE-I/-II (Di Martino et al. 2017), CoRR (Mennes et al. 2013, Zuo et al. 2014)], the Nathan Kline Institute Rockland Sample (Nooner et al. 2012), the Healthy Brain Network (Alexander et al. 2017), and ENIGMA (Medland et al. 2020, Thompson et al. 2020). We have previously described the benefit of shared data in brain imaging, highlighting the increased engagement of scientific disciplines and increased scale of sample sizes without compromising publication rate or journal impact factor (Milham et al. 2018).

Importantly, longitudinal studies in DCN are by nature repeated measures and can dramatically improve statistical power and reliability. Repeated measures can have dramatic effects on power. Increasing the number of follow-up or baseline measures severalfold can reduce sample size requirements by 35–70% (Vickers 2003). Indeed, because of their sheer size and breadth, both the ABCD and upcoming HBCD studies noted above have put DCN at the forefront of the study of cognition in general—a major strength of the field.

Overall, these various big data–inspired efforts are not only challenging researchers to build the infrastructure and methods required for supporting the aggregation, harmonization, and sharing of large-scale data sets, but also challenging them to think through differences in study designs (e.g., sampling) and methods (e.g., imaging sequences, clinical characterizations, questionnaires) across studies and how to deal with variations in data quality and errors when they arise. If successful, the end result of this process will be an optimized model for harmonized data acquisition, aggregation, and sharing, which in turn will enable the amassment and analysis of the large-scale data sets needed to achieve findings that are useful (e.g., neuroscientifically, clinically), representative, and reproducible.

3.1.4. Bridges of scale from humans to animal models. A growing number of investigators have recognized the importance of relating human cognitive neuroscience findings to the underlying neurobiology and neurophysiology of the brain. Many of the tools required for relating systems-level brain organization to neurophysiology are only available in animal models. Over the last decade, techniques for assessing brain physiology with fMRI in laboratory animals have been greatly refined (Miranda-Dominguez et al. 2014, Ramirez et al. 2020, Stafford et al. 2014, Xu et al. 2020) and models for promoting harmonization, data sharing, and collaboration in the nonhuman communities established [e.g., PRIMatE Data Exch. (PRIME-DE) Global Collab. Workshop and Consort. 2020)]. Our progress in establishing more appropriate animal models for neurological and psychiatric conditions is accelerating bench research-to-human health translation (Assaf et al. 2020, Gozzi & Schwarz 2016, Schaeffer et al. 2020) and informing evolutionary perspectives of brain development (Schaeffer et al. 2020). For example, recent nonhuman primate models using chemogenetic tools have clearly highlighted the broad effects that focal disruptions have on noninvasive measures of function (Grayson et al. 2016)—meaning the lesion does not necessarily line up with what is seen on functional imaging—which is very important context when interpreting findings in cognitive neuroscience with the same techniques. The neurobiology of fear and its development in DCN have greatly benefited from cross-species studies and collaboration and provide one of the strongest examples of how to design and leverage distinct scientific capabilities across species (Callaghan et al. 2019).

3.1.5. Greater involvement of nontraditional organizations in cognitive neuroscience. A final strength of DCN worth highlighting is the heightened emphasis on outreach and engagement with public-private partnerships, nonprofit organizations (e.g., Flux Society, Child Mind Institute, Masonic Institute for the Developing Brain, Montreal Neurological Institute), and patient/public health advocacy groups (such as the National Scientific Council on the Developing Child). The strengthened ties between developmental cognitive neuroscientists and community

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organizations maintain focus on the importance of translating academic findings into meaningful policy and health care actions. Advancing developmental cognitive neuroscience beyond the academic sphere also expands opportunities for long-term support, as exemplified by collaborations with Google (e.g., Google Research outreach), Apple (e.g., Apple Reach), and other companies to develop tools to support learning, health, and wellness.

3.2. Weaknesses

While functional networks provide a uniquely powerful lens through which to understand brain development, the progress enabled by the strengths listed above is limited by several important methodological challenges and conceptual issues that cannot be overstated.

3.2.1. Erosion of the ties among psychology, computational methods, and neurobiology. Although beneficial in many respects, cross-disciplinary excitement and novel methods have moved DCN further away from its foundations in psychology and neurobiology. As neuroimaging data have become more accessible and the size, breadth, and complexity of these data sets has expanded, DCN has naturally grown to include more scientific disciplines. Equally as important, it has leveraged the growing availability of data to complement long-standing hypothesis-driven approaches to cognitive neuroscience with a framework for implementing discovery science, which many have long resisted. Such shifts in demographics and thinking are essential for progress and are a noted strength of DCN. However, at the same time, this change in demographics has fueled a shift away from many of the concepts and foundational principles in basic neuroscience and psychology that started DCN 50 years ago. In addition, the increased focus on discovery science has raised concerns about how to deal with new black box approaches (e.g., deep learning and machine learning). For example, Miranda-Dominguez et al. (2014) published a paper titled *Connectoyping: Model Based Fingerprinting of the Functional Connectome*, which highlighted that FC MRI data are able to obtain a personalized connectivity profile for an individual such that, with 100% accuracy, that individual could be identified on unique days—i.e., a functional fingerprint. The paper highlighted that this could be completed with limited amounts of data and that frontoparietal systems were highly variable among individuals. Later, these findings were popularized and replicated with traditional FC and machine learning techniques in a highly successful series of publications beginning with Finn et al. (2015). Recently, fingerprinting has been described as reliable from adolescence to adulthood with consideration of cognitive and default networks (Jalbrzikowski et al. 2020).

However, as the idea of functional fingerprinting has expanded from predicting brain–behavioral relationships and into areas of development, the field has often attributed brain features utilized to maximize prediction as the surrogate functional neuroanatomy associated with behavioral performance, often with patterns in the features that bear little resemblance to known functional neuroanatomy. Simply put, classification problems do not require all of the detail or precision of the associated systems to either classify an individual or predict their behavioral performance (see, e.g., Fair 2018). Because only partial information is required and functional imaging data are relatively noisy, the features selected often do not represent the true underlying functional neuroanatomy associated with the behavior. They are also likely to be unreliable, meaning that the same prediction accuracy in different samples may yield distinct sets of features (Tian & Zalesky 2021). These realities should not take away from the importance of models attempting to maximize classification or predictions—as with many questions, prediction accuracy, as opposed to understanding the detailed functional neuroanatomy, is the primary goal. A deeper focus on known anatomy and neuroscientific principles will enhance the benefits to DCN of advanced

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computational methods. Maintaining the founding principles of DCN while simultaneously expanding the breadth of approaches is important for the future success of DCN (Goldman & Fee 2017).

3.2.2. Insufficient cross-disciplinary training. The increased breadth of developmental cognitive neuroscience, now ranging from developmental psychology and neuroscience to physics and applied math, has created new challenges for training programs. Current training curricula can struggle to provide cognitive neuroscientists with the requisite training in cell and molecular biology and experimental psychology as well as cutting-edge computational and biostatistical methods (Akil et al. 2016, Goldman & Fee 2017). Trainees and mentees may be encouraged to consider these courses and functional roles as electives, if at all, but engagement and degree of engagement are not consistent and may be influenced by mentor expertise at the graduate student and postdoctoral level (Liénard et al. 2018). Although cross-disciplinary intersection is a strength of DCN, the practice of individual researchers with focused expertise contributing independent components may not provide the holistic, integrated, standardized, and reliable analyses crucial to propelling understanding of brain–behavior relationships (Sahneh et al. 2021). There is a fear that without cross-disciplinary training, or at minimum close collaboration across disciplines, several unintended consequences might occur. For example, DCN has frequently taken in methods and analytical approaches from other areas of science that had been developed under specific conditions, not necessarily in the same context as DCN (e.g., smaller samples, systematic confounds, head motion). In some cases methodologies are exceedingly difficult to reconcile with known neurophysiology, such as with the indirect relationship of neural activity and the BOLD response (along with the relatively slow and temporally smoothed nature of the BOLD response). Avoiding misuses of advanced computational methods and facilitating efficient and important discoveries requires proper cross-disciplinary training and collaboration.

3.2.3. Head motion distortion of fMRI/resting-state functional connectivity data. Poor data quality is a primary obstacle for studies of brain network development (Power et al. 2014, 2015; Satterthwaite et al. 2019). In children and adolescents, data quality is mostly driven by in-scanner motion, which is significantly correlated with age, gender, cognitive measures, and the presence of neurodevelopmental disorders (Dosenbach et al. 2017, Siegel et al. 2017). Motion artifacts systematically distort measures of FC, but task fMRI and structural metrics are also affected (Power et al. 2012, Satterthwaite et al. 2012, Siegel et al. 2017, Van Dijk et al. 2012, Yan et al. 2013).

Thus, in-scanner motion mitigation is particularly important for developmental neuroimaging studies (reviewed in Bassett et al. 2018) and most analysis methods implement postprocessing strategies to identify and correct for motion artifacts (Jo et al. 2013, Satterthwaite et al. 2019, Yan et al. 2013). fMRI data acquisition strategies that aim to correct for head motion distortion during the scan are also under evaluation (Lanka & Deshpande 2019). In addition, displaying real-time head motion information to MRI scanner operators (Dosenbach et al. 2017) and study participants (Greene et al. 2018, Fair et al. 2020) reduces motion at the source through behavioral interventions. While motion mitigation is an absolute must for all neuroimaging research, clearly it must be recognized that motion correction has the potential to introduce bias into studies of typical and atypical development (Marek et al. 2019, Satterthwaite et al. 2019, Siegel et al. 2017).

The recognition of systematic, reproducible motion distortion has inspired a series of methodological studies that seek to limit the impact of motion artifacts (Griffanti et al. 2014, Hallquist 2013, Patel et al. 2014, Pruim et al. 2015). New techniques using multiecho pulse sequences and multiecho independent component analysis (ICA) denoising strategies are growing in popularity because they seem to improve the separation of noise from neuronal physiology

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(Lynch et al. 2020). For structural MRI scans, prospective motion correction relying on volumetric navigators has shown promise in adult volunteers (Tisdall et al. 2016); the same approach should also benefit developmental studies. Combining motion sensing and correction methods with real-time motion feedback to the scanner operators and study participants optimizes imaging workflows and helps maximize the amount of usable MRI data collected during each visit, both of which are critically important for advancing DCN research (Dosenbach et al. 2017, Fair et al. 2020, Greene et al. 2018).

3.2.4. Poor replicability and reproducibility. Many brain–behavior associations have failed to reproduce (Boekel et al. 2015, Genon et al. 2017, Kennedy et al. 2019, Kharabian Masouleh et al. 2020). There are likely several reasons why reproducibility has been an issue for many studies to date (Button et al. 2013, Ioannidis 2005). For one, as noted above, the SNR of many brain and behavioral measurements is relatively low and has led to long-standing concerns about the reliability of neuroimaging modalities, particularly fMRI and diffusion MRI. In its simplest form, reliability can be defined as the ability to give consistent measures either over time (e.g., days, weeks) or across raters (e.g., scanners, acquisition protocols) (Zuo et al. 2019b). Reliability is one of the key determinants of sample size requirements for detecting effects of a given size with sufficient power and of the sensitivity of any measure to individual-level differences (e.g., for biomarker discovery, laboratory testing, growth charts). Low-reliability data increase the risk of false negatives as well as the potential for spurious findings.

Sample sizes previously typical for cognitive neuroscience population studies (median fMRI study $N = 25$) have been underpowered for reproducibly detecting associations between cognitive measures or psychological symptomatology and brain metrics (Biswal et al. 2010; Button et al. 2013; Kennedy et al. 2019; Marek et al. 2019, 2020; Smith & Nichols 2018; Van Horn & Gazzaniga 2002). As sample sizes increase, the predictive accuracy of reported models decreases (Sabuncu & Konukoglu 2015). Most studies that show poor reproducibility have fewer than 1,000 participants.

In the context of small brain–behavior effect sizes and small samples, the variations in data processing are also likely to influence reproducibility. Botvinik-Nezer et al. (2020) showed the effects of differences in analysis methods on task fMRI findings. They had 70 different teams of researchers analyze the same neuroimaging data set under the same extant hypotheses. The fMRI results were highly variable across teams, depending on the chosen data processing strategies. Efforts are under way to reduce variability introduced during data processing by improving and standardizing analysis procedures (**https://www.nipreps.org/**).

Over the past decade, a shift away from the study of central group tendencies, which are highly reliable, toward associating individual differences in brain metrics with individual differences in cognitive traits has contributed to a reproducibility crisis. Cognitive neuroscience may benefit from lessons learned in genetics, where small studies of candidate genes with limited replicability evolved into GWA studies of very large samples ($N > 100{,}000$) with much improved replicability (Zuo et al. 2019a,b).

As highlighted in recent studies (Alexander et al. 2020, Milham et al. 2021, Zuo et al. 2019b), concerns regarding reliability are not limited to biological measures. Cognitive performance measures may be among the most worrisome as tasks rapidly adapted from cognitive neuroscience are rarely assessed for the reliability with which they can measure individual differences and, at times, are used despite knowledge of poor reliability. Psychometrically sound psychiatric questionnaires can become problematic when added to population studies as they were designed to assess symptoms or weaknesses, leading to truncated response distributions with large portions of the sample exhibiting little to no variance, limiting their utility. Recent work has demonstrated the feasibility and utility of creating questionnaires with a symmetric distribution in healthy populations.

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3.3. Threats

As we look beyond our community, we face numerous threats in conducting and evaluating science, as well as in training future scientists, that are common to many scientific disciplines.

3.3.1. Publication bias. The predictive models with large effect sizes currently prevalent in the literature are at least in part a consequence of publication bias in favor of large positive findings (Chuard et al. 2019, Head et al. 2015, van Zwet & Cator 2020), thus spuriously inflating reported effect sizes (Sabuncu & Konukoglu 2015, Smith & Nichols 2018, Walum et al. 2016).

3.3.2. Current funding structure not designed to support the open research efforts required to boost reproducibility and ecological validity. Large data sets and powerful computational infrastructure are critically important for realizing the full potential of modern cognitive neuroscience. However, the traditional single investigator award designed to support traditional cognitive neuroscience research that dissects neuropsychological processes using within-subject measures (e.g., task fMRI) cannot support the massive resources required for BWA studies. Conducting BWA study analyses on data sets collected with the funds available for single investigators likely only perpetuates the weaknesses stated above. Furthermore, data sharing collaborations can create budgetary and logistical complexities that can be discouraging without the proper infrastructure and funding via public and private agencies. Carefully considering which types of questions can be tackled with traditional funding mechanisms and which cannot while maximizing collaboration and data sharing are vitally important for progress.

3.3.3. Lack of diversity in study teams. Lack of study team diversity contributes to uneven recruitment among research participants, limits scholarly perspectives, and enables implicit bias in citation practices (Bertolero et al. 2020). Although neuroscience is one of the fastest growing research disciplines, the proportions of non-White and female neuroscientists decrease with career advancement (Jones-London 2020). Thus, non-White and female scientists are less likely to be grant recipients and principal investigators responsible for experimental design and training, further perpetuating health disparities and inequities in science.

Maximizing progress will not come from a homogeneity of ideas, thoughts, education, experience, and culture. Research teams without a broad range of experience may miss out on opportunities for discovery.

3.3.4. Conflicting incentives for career advancement. Academia as an institution has established metrics for success that disincentivize adopting new ways of conducting science and diversifying the workforce. The pressure to establish oneself as a lone expert in a novel aspect of the discipline and to operate within departmentally and/or institutionally defined research silos (So Long to the Silos 2016, Bijsterbosch et al. 2020), discourages efforts to gather large data sets or generate novel tools using resources shared among multiple collaborators. In addition, as an investigator pushing toward promotion, there is very little incentive to promote diversity. Academic institutions often highlight how they value diversity, equity, and inclusion (DEI), yet specific work by faculty to promote DEI is rarely considered or heavily valued as part of the promotion process. However, some universities are beginning to challenge the institutional policies that focus purely on teaching, research, and service to also include DEI work as part of the promotion guidelines (Khalid & Snyder 2021).

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3.3.5. Competition to attract and retain talent. Even if training curricula are updated and career incentives restructured, attracting and retaining top talents in DCN are still critically important. A skilled data scientist is valued in many organizations that can offer better compensation and work–life balance competitive with research institutions. According to the US Bureau of Labor Statistics, computer and information research scientists earned a median annual salary that was twice the 2019 national average and twice the 2019 average NIH postdoctoral training salary (Year 1) (US Bur. Labor Stat. 2021). Combining the inconsistent appreciation of data scientists in academia (Rodríguez-Sánchez et al. 2017), the relatively low odds of success of academic trainees in achieving long-term research careers, the impact of the coronavirus disease 2019 (COVID-19) pandemic on academic hiring (Gould 2020), and the continued demand for data scientists in industry (Press 2020), we face great challenges in recruiting and retaining talented researchers.

3.4. Opportunities

The current environment of public policy, biomedical research initiatives, and education provide numerous opportunities that can mitigate the challenges and threats to DCN.

3.4.1. Individual-specific precision medicine for diagnostics and treatment. The efforts of precision medicine research and therapy in oncology provide valuable lessons for other clinical applications (Ashley 2015, Cutler 2020), including DCN. Specifically, the recent generation of stable, patient-specific connectomes using noninvasive imaging opens up the possibility of addressing individual differences in behavior and clinical conditions (Laumann et al. 2021, Satterthwaite et al. 2018).

3.4.2. Big data resources and open sharing structures provide opportunities to scale up consortium efforts. Momentum for open science is growing with the endorsement of data management standards [such as Findability, Accessibility, Interoperability, and Reuse (FAIR)] and code standardization by national and international research bodies (Byrd et al. 2020, Data Sharing 2018, Popkin 2019). The already established efforts to create and share large data sets and open code within cognitive neuroscience (described in Section 3.1.3) provides us with the opportunity to be among the leaders in making open science into typical practice, applying best practices from GWA studies and genomics (Choudhury et al. 2014). For example, the launch of the HBCD study was strongly influenced by the success of the execution, data sharing, and communication of the ABCD study (Hoffman et al. 2018; Volkow et al. 2018, 2020).

3.4.3. Multimodal assessment. It is critical to note that while the current review is written through the lens of neuroimaging, we do not intend to suggest that this tool or field alone could achieve the goals of DCN. In fact, it is quite the opposite. Numerous modalities have promise for developing objective markers of brain and behavioral development (e.g., actigraphy, ecological momentary assessment, eye tracking, EEG, electrodermal activity, heart rate variability, immunological assays), each offering a unique perspective. Too often these technologies and methods are studied in isolation from one another, yielding fragmented perspectives of development and suboptimal indices of individual variation. It is our belief that one of the greatest opportunities for advancing the field will lie in the adoption of multimodal assessment strategies capable of providing multilevel perspectives of brain development, function, and dysfunction. In selecting among modalities to pair with one another, it will be essential to consider their reliability and validity to avoid repetitions of past missteps in the field.

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3.4.4. Initiatives to diversify subject populations and minimize health disparities. In 2019, Martin et al. (2019) reported that 79% of participants in GWA studies were of European descent, highlighting the lack of broad ethnic representation across study participants and bias toward European ancestry. There are a growing number of programs now to address the need to educate, recruit, and include a broader sample of the population in human health studies, including NIH's All of Us program, the Hispanic Community Health Program, and the African American Cardiovascular Pharmacogenomics Consortium. Specific to neuroscience, Barnes & Bennett (2014) note a lack of research participation among African Americans in Alzheimer's disease studies despite an estimated 2–4 times greater risk of developing Alzheimer's disease or a related dementia (Barnes & Bennett 2014, Kunkle et al. 2021, Morris et al. 2019). Therefore, efforts to increase research (e.g., by the African Ancestry Neuroscience Research Initiative), education, and recruitment within the African American community and other underrepresented populations are vital (Couzin-Frankel 2019, Gilmore-Bykovskyi et al. 2019, Green-Harris et al. 2019). We have already taken small steps toward a long-needed correction in neuroimaging studies as the ABCD study, while not perfect, has aimed to provide a comprehensive characterization of adolescent development in a sample that reflects the sociodemographic variation of the US population at recruitment completion (N = 11,875; 52.1% White, 15.0% Black, 20.3% Hispanic, 2.1% Asian, and 10.5% other) (Karcher & Barch 2021). Furthermore, recent COVID-19 pandemic adaptations to education, engagement, and patient management provide opportunities to widen outreach to marginalized communities in DCN.

3.4.5. Support for diversifying the scientific workforce. Team diversity boosts productivity and progress. To recruit and maintain diverse talent, we need to value diversity proportional to its importance. There is growing collective awareness and widespread support to diversify research teams, leadership panels, and participant outreach as represented by numerous launched initiatives at the national level (e.g., NIH FIRST Program, NSF Includes). Beyond the National Institute of Neurological Disorders and Stroke (NINDS) Diversity Awards, the NINDS has also proposed a model within its Office for Programs to Enhance Neuroscience Workforce Diversity that includes identifying diverse pools of trainees, providing resources and addressing barriers in career transition, developing meaningful mentorship, and practicing policies to enhance diversity (Jones-London 2020). In addition, there are opportunities to partner with undergraduate programs reinforcing at-promise youth in science, technology, education, and math, such as the Meyerhoff Scholars Program (Maton et al. 2016). We would be well served to utilize this framework to establish strategies for fostering well-rounded talents along their career trajectories that go well beyond these initial steps. The existing programs can provide resources and tested methods for bolstering our existing DEI efforts in DCN in addition to launching new collaborative initiatives.

4. CONCLUSIONS

The field of cognitive neuroscience and, in particular, DCN, continues to evolve in ways that its founders may not have anticipated nearly 50 years ago. DCN has grown considerably and continues to rapidly expand in innovation and discovery. Yet these approaches require modernization of sample collection, experimental design, and analysis for brain networks and systems to inform characterization of complex behavioral phenotypes. As our research expands in breadth and depth, it is critically important to maintain a solid grounding in the principles of neuroscience and psychology that form the basis of cognitive neuroscience. To keep pace with rapidly advancing computational methods without forsaking our founding principles will require large shifts in institutional culture, funding strategies, and training that should be guided by leaders in our

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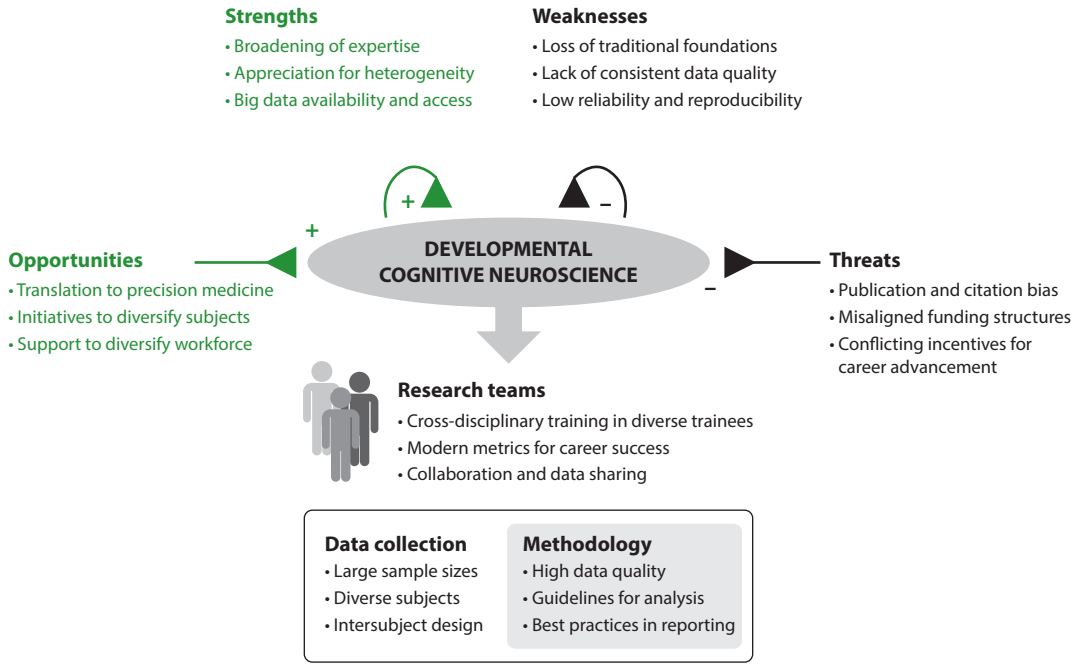

Figure 4

Strengths, weaknesses, opportunities, and threats analysis for the field of development cognitive neuroscience. Future efforts in scientific training, analysis, reporting, and career advancement should consider internal factors (strengths and weaknesses) and external factors (opportunities and threats) to pursue the mission of cognitive neuroscience in the modern environment of big data.

field—items laid out in the SWOT analysis above (**Figure 4**). Fortunately, talented junior investigators and trainees are flocking to DCN. They are embracing change and eager to take on the challenges and opportunities our discipline faces in the era of big data and networks.

DISCLOSURE STATEMENT

D.A.F. and N.U.F.D. have a financial interest in NOUS Imaging, Inc., and may financially benefit if the company is successful in marketing Framewise Integrated Real-Time MRI Monitoring (FIRMM) software products. D.A.F. and N.U.F.D. may receive royalty income based on FIRMM technology developed at Oregon Health and Sciences University and Washington University and licensed to NOUS Imaging, Inc. A.H.M, T.S., and M.P.M. are not aware of any affiliations, memberships, funding, or financial holdings that might be perceived as affecting the objectivity of this review.

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