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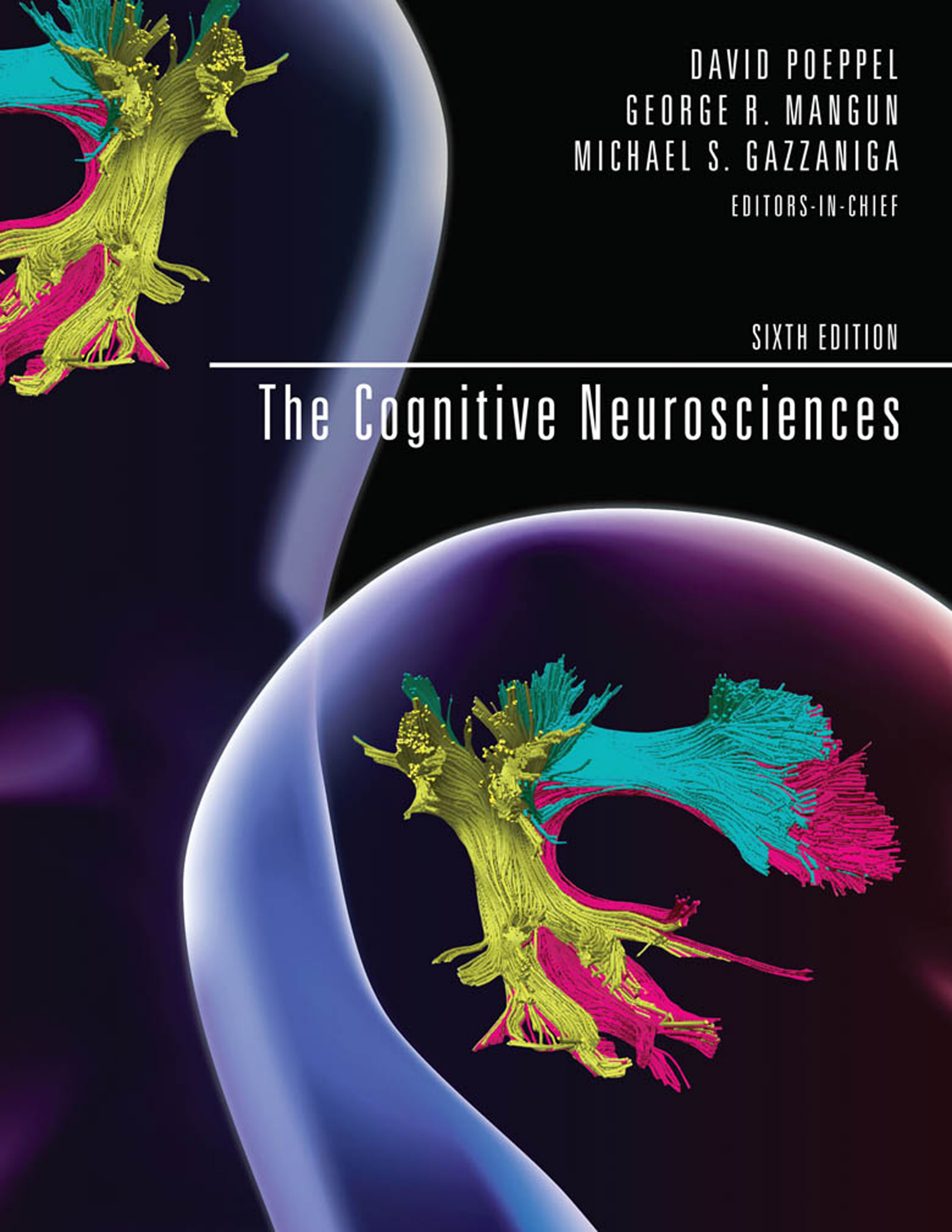

97 Toward a Socially Responsible, Transparent, and Reproducible Cognitive Neuroscience

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ABSTRACT As members of the next generation of leaders, we aim to promote an ethical, inclusive, humanistic, and curiosity-driven code of conduct within cognitive neuroscience. We critically examine the current state of the field and discuss issues that remain to be addressed. In particular, we highlight the need for cultural change, including a greater focus on integrity and accountability (i.e., addressing sexual harassment), as well as promoting diversity. Further, we highlight current methodological considerations, such as big data and deep data, replicability, and reproducibility. We consider some of the unresolved controversies within cognitive neuroscience and where the research should go from here. Finally, we delve into how neuroscience research is presented to the public and how science communication can benefit society. This chapter presents a call to action not only to further scientific improvements but also to address biases and behaviors that have the potential to hinder scientific advancements.

The previous chapters discussed current directions in cognitive neuroscience. The goal of the current chapter is to address critical issues that limit progress in our field. Scientific progress depends not only on methodological and conceptual improvements, but also on the ethical conduct in science. Therefore, before addressing methodological issues we first discuss two cultural barriers that have impeded the inclusivity of scientific training and contribution. In particular, we highlight the prevalence of sexual harassment and the pervading lack of diversity.

Integrity and Accountability

Whereas ethical issues such as data falsification and plagiarism are typically referenced in discussions on scientific integrity, cultural issues such as sexual harassment and assault are often discussed separately or overlooked entirely. However, more than 50% of female faculty and 20%–50% of female students—with higher rates for women of color and members of the LGBTQ+ community—have reported experiencing gender-based harassment, unwanted sexual attention, and/or sexual coercion (National Academies of Science, Engineering, and Medicine, 2018)—figures that are likely underestimated when considering the fear of retaliation. The innumerable cases of sexual misconduct that have emerged in recent years indicate that our field, like many others, is in need of a critical reevaluation of its ethical practices. Several features inherent to our academic community contribute to an environment where sexual misconduct has become normalized. These include (1) male-dominated work settings, (2) hierarchical power structures, (3) institutional tolerance of sexual harassment and gender-based discrimination, (4) a focus on protecting the liability of institutions, and (5) a lack of informed and proactive leadership. Sexual harassment and assault have an impact on physical, emotional, and professional well-being—and in doing so, obstruct the growth of the field. Thus, we argue that sexual misconduct in academia should be treated as an issue of scientific misconduct (see National Academies of Sciences, Engineering, and Medicine, 2018, pp. 114–118, for further discussion). The responsibility to alleviate these hindrances lies with the scientific community as a whole. The first steps toward this goal include informing the community, changing institutional policies (Melnick, 2018), redefining scientific integrity to include gender-based issues, and reinforcing accountability at all levels.

Equality in Science

The state of diversity and equity within cognitive neuroscience warrants change. Recently, at the 2018 Kavli Summer Institute in Cognitive Neuroscience, a hotel receptionist was asked to contact one of the invited speakers, assumed that Dr. X could not have been the female voice who answered the phone, and asked to speak to her husband. Considering that women make up half of the contributors to this book, including half of the young neuroscientists coauthoring this chapter, it is easy to assume that these unconscious biases will subside. However, the lack of diversity and equity in science is systemic—it is not solely an individual but also a policy failure. The current system favors elite education; disadvantages low-income and first-generation students with few paid opportunities for research experience; reinforces the pay gap; offers poor maternity and paternity leave policies; has a gross underrepresentation of people of color in faculty positions that is often accompanied by greater service expectations; is heteronormative, with diversity initiatives omitting LGBTQ+ scientists (Freeman, 2018); and focuses on experimental results obtained from individuals of higher socioeconomic status (see chapter 90). Achieving participation in a science that represents society as a whole is more than just moral or ethical. It is how we produce the *best* science. Research suggests that groups that are ethnically diverse have higher citation counts on average than homogenous ones (Powell, 2018)—just one demonstration of the value of diversity in high-impact science. Change is necessary. As long as we as scientists remain silent amid this systemic failure, we tacitly propagate it.

Call to Action

We challenge all scientists, especially those in positions of power and influence, to recognize the responsibility of actively promoting a diverse academic and professional environment that supports ethical codes and prevents harassment and discrimination. The failure to take on these challenges perpetuates the sociocultural mechanisms through which sexual harassment and systemic underrepresentation occur. We caution against the unfair enforcement of policies based on individuals' institutional influence or demographics (e.g., gender) and against creating discretionary internal committees in lieu of transparently and publicly acknowledging these issues that affect the quality and integrity of science. Bystanders, potential aggressors, and those benefiting from societal privilege should accept personal responsibility to educate themselves on these issues.

Current Approaches in Cognitive Neuroscience: Big Data and Deep Data

The term *big data* has become a buzzword with multiple definitions; here, we adopt Yarkoni's (2014) definition that refers to data sets of a magnitude considered unusual for the field. Big data can address the lack of replicability, reproducibility, and statistical power from small sample sizes. Larger samples ensure that effect-size estimates and statistical effects can be more accurately captured. Moreover, the practice of validating predictions out of sample, as opposed to within-sample correlations, distinguishes the big data approach from its counterparts and presents an advantage in establishing both the reliability and generalizability of results.

Big data improves the ability to characterize individual differences across participants, which is critical for the successful real-world application of neuroscience research. Individual differences are often examined in models testing mediators and moderators, which require large sample sizes. Hence, big data is ideal for testing such models and reduces the risk of type II errors. However, large-scale studies using cross-sectional designs do not allow for causal inference, which may be better suited for longitudinal analyses (see the next section). Also, since large sample sizes can make trivial effects statistically significant, estimating—and inferring the potential meaning of—effect sizes becomes crucial for the interpretation of results. In the coming years, the collection of big data will continue through initiatives such as the Brain Activity Map (Kandel, Markram, Matthews, Yuste, & Koch, 2013) and the Brain Research through Advancing Innovative Neurotechnologies (BRAIN) Initiative (Choudhury, Fishman, McGowan, & Juengst, 2014).

Additionally, data can be collected across large timescales (e.g., days and years) within single subjects as part of longitudinal or *deep data* collection. This allows for the study of dynamic changes in brain connectivity, gene expression, and metabolites within a single subject (Poldrack et al., 2015).

Application of Deep Data to Development and Neurocognitive Theories

Longitudinal studies involve the collection of behavioral and neuroimaging data at several time points throughout an individual's lifetime and enable researchers to study, track, and predict changes in brain structure and function across the life span. Additionally, the use of longitudinal (vs. cross-sectional) data allows researchers to test for nonlinear trends in how various neuroanatomical measures (e.g., cortical thinning, gray matter volume) change over development. Moreover, longitudinal designs have an increased capacity over cross-sectional designs to distinguish between within- and between-subject variation (Rogosa, Brandt, & Zimowski, 1982). Each additional repeated measure substantially increases both the ways to model change and the number of available models (King et al., 2018).

Recent and ongoing large-scale neuroimaging studies employ longitudinal sampling of individuals. For example, the MyConnectome project demonstrates dynamic changes in brain connectivity, gene expression, and metabolites in a single person over an 18-month period (Poldrack et al., 2015). Similarly, the Adolescent Brain Cognitive Development study (ABCD) plans to collect longitudinal data from over 10,000 individuals, 9–10 years old, across the United States as they progress into early adulthood (Casey et al., 2018). Meanwhile, in Europe, the Lifebrain research project will collect neuroimaging measures at six time points from birth to age 100. The longitudinal effects observed in these decades-long undertakings will help identify and track life span changes in brain structure and function and will inform our understanding of how environmental, genomic, and experiential factors shape brain development.

These studies are influential for developing theories of how brain function and organization change over time, which is also critical for understanding human development. Developmental studies seek to understand how a particular neurocognitive characteristic or process changes throughout an individual's lifetime and to identify genetic and environmental factors that predict individual differences in how such changes vary across people. In addition, they allow us to validate psychological and neurocognitive theories across the life span to address whether these theories can accommodate data beyond those measured in healthy, adult-aged samples.

The life span perspective also helps researchers track the onset and progression of mental disorders and neurodegeneration. In particular, aging has been characterized as an unprogrammed, stochastic wear-and-tear process manifesting in nonlinear and accelerated impairments such as reduced myelination, thinning dendritic spines, and axon deformation (see chapter 6). These quasiperiodic changes occur throughout the life span and must be frequently measured in the same individual in order to chart their progression.

Logistics of Large Data Projects

Future research in cognitive neuroscience will likely require a combination of both big and deep data approaches. These projects often involve collaborations across multiple departments and institutions. Thus, many factors should be considered before undertaking such projects, including determining sample sizes based on a priori power analysis, budget allocations, ethical data-sharing practices, authorship order, preference for theory- versus data-driven approaches, and procedural standardization.

Standardization reduces the risk of confounds related to site differences and should be monitored as these studies progress. Nevertheless, regional differences between participants may remain, making site location an important covariate when examining across-site results. Taken together, these challenges can be time-consuming and require ongoing discussion. However, addressing them will result in better classification of individual differences, as well as more precise translational applications.

Pioneering efforts like the fMRI (functional magnetic resonance imaging) Data Center (Van Horn & Gazzaniga, 2002) have created repositories for neuroimaging data sharing. Although most agree that researchers have an ethical responsibility to share data (Brakewood & Poldrack, 2013), only half report doing so, even though 85% express a willingness to use others' data if easily accessible (Tenopir et al., 2011). The tepid (but growing) consensus to share data is likely related to the providers' confidence in their data sets and results (Wicherts, Bakker, & Molenaar, 2011). However, with over 60,000 practitioners of neuroscience contributing to the field, many will add to the integration of our vast menageries of data scattered across labs around the globe. As Henry Markram predicts, "All the signs indicate that this new generation of neuroscientists will be far more ready to work in teams than the current generation. This is our true hope for the future" (Kandel et al., 2013).

Replicability and Reproducibility

Replication, the ability to obtain similar results when repeating experiments, is a cornerstone of scientific knowledge. In 2015 Brian Nosek and colleagues from the Open Science Collaboration attempted to replicate 100 experiments published in high-impact psychology journals. They found that only 39% of their data sets replicated the original findings at the standard significance level. Standard hypothesis-testing approaches were criticized as early as 1967 by Paul Meehl, and statisticians and research bloggers have voiced concerns about replicability for years. However, Nosek and colleagues highlighted the scope of the problem, and replication has now become a common topic of conversation among scientists and a staple in contemporary research methods courses.

Incentives to report positive rather than negative findings directly contribute to the replication crisis. The current standards arbitrarily define an alpha level of 0.05 and regard findings below this threshold as "significant." These conventions encourage selecting results post hoc with $p < 0.05$, often without correcting for multiple statistical comparisons. These problems are referred to as data dredging, *p*-hacking, or, less reproachfully, "the garden of forking paths," reflecting the numerous ways in which one can reasonably preprocess or frame the data analysis until statistically significant results are found (Gelman & Loken, 2013).

At the individual level, we believe the most important solutions to the replication crisis are preregistration and publicly releasing both data and code. In preregistration, authors explicitly and precisely state their methods and hypotheses before running the study. Exploratory analyses are acceptable at later stages but must be acknowledged as such rather than spun into a story about how they were predicted from the outset. Ideally, original findings in exploratory analyses would be followed up with replications using novel data sets.

At the institutional level, journals are often reluctant to publish negative results that are perceived as less exciting or a reflection of poor methodological rigor. Therefore, grant agencies must increase funding for replication efforts of seminal studies with large sample sizes, and journals might agree to publish data before they are collected in order to incentivize researchers to precisely report their findings. Hypothesis testing within these studies may be improved by focusing on Bayes factors or posterior summaries derived from well-defined models (Benjamin et al., 2018), while others have proposed an emphasis on effect sizes rather than null hypothesis significance testing (Szucs & Ioannidis, 2017). Finally, in order to improve the replicability of science, the incentive structure of academia must change. The current incentive structure rewards individual productivity (i.e., number and frequency of publications) over more collaborative "slow science." By shifting incentives away from fast science at the individual level, the field will be better positioned to replicate and extend previous findings through slower and more deliberate collaborative efforts.

Complementary to replicability is reproducibility: the duplication of results given the same data set. In recent years reproducibility has been facilitated by websites like Open Science Framework (https://osf.io) and GitHub (https://github.com) that allow researchers to publicly release their data, experimental and analysis code, stimuli, and other task-related documents. Additionally, the increasing use of open-source languages like Python and R has improved the accessibility of scientific tools. Collectively, these recent efforts should improve the quality of code and the reliability of results prior to publication and ensure that independent labs can reproduce the results.

Improving reproducibility would also influence training for the next generation of cognitive neuroscientists. The classroom is an ideal setting for utilizing these software tools and databases. Research methods courses can directly access data sets, analyses, and experimental protocols from open-access resources to teach new concepts while simultaneously testing the reproducibility of findings in the field. The availability of such materials provides an explicit demonstration of how science (and open science) is conducted, which in turn helps trainees develop into independent researchers who will implement similar techniques.

Choosing Your Method Wisely

Neuroimaging methods have substantially evolved over the past three decades, and the pace at which new methods appear is rapidly increasing. However, rather than being seduced by novel tools and techniques, it is worth reflecting on what new methods can and cannot tell us. Despite much progress, most of the measures we use to infer brain structure and/or function are imperfect proxies for brain activity. For instance, fMRI measures levels of blood oxygenation (BOLD) rather than direct neural activity, and water diffusivity is used to infer white matter microstructure, yet very little is known about how different microstructural properties influence diffusivity. Furthermore, few studies have mapped other measures at the macrostructural level, such as gray matter volume, to microcellular indices (Mills & Tamnes, 2014). Given these shortcomings, when MRI measures are used to build complex network models, every additional analysis step abstracts further from the biological mechanisms of interest.

Researchers estimating brainwide functional and structural connectivity using resting-state fMRI and diffusion tractography should also consider model assumptions and measurement. Functional connectivity first depends on evidence of monosynaptic connection between targeted brain circuits, as in axon-tracing studies of animals. Then, evidence of conditionally dependent activity between circuits, as in studies involving physiological manipulation (e.g., electrophysiology, optogenetics), can further guide researchers' inferences from functional correlation to functional connectivity.

A second consideration in studies of brain connectivity is the operationalization of structural connectivity. Researchers can index structural connectivity with results from diffusion tractography, such as the number of fibers, length of fibers, and water diffusion along fiber trajectories. However, these measures might not estimate structural connectivity with equivalent anatomical precision. The number of fibers traced between brain circuits is a function of manually selected parameters in tractography algorithms, and the length of fibers is a function of the ease of tracking fibers across brain terrain containing simple versus complex fiber crossings. In contrast, measures of water diffusion, such as fractional anisotropy and mean, axial, and radial diffusivity, can be validated with invasive studies of axon myelination and density (e.g., electron microscopy). As modeling approaches to neuroimaging data evolve, so must conceptual clarity about brain connectivity.

Modalities such as fMRI, electroencephalography (EEG), and magnetoencephalography (MEG) are sensitive to different aspects of brain activity with varying spatiotemporal resolutions. Thus, combining these modalities is critical for a complete picture of brain activity. One multimodal approach combines MEG and fMRI under the framework of representational similarity analysis (Cichy, Pantazis, & Oliva, 2014). The latent neuronal space can also be used as the common ground for combining multimodal neural signals, as demonstrated with BOLD fMRI and local field potentials (Hermes, Nguyen, & Winawer, 2017). Moving forward, machine learning (Baltrušaitis, Ahuja, & Morency, 2019) can also be used to develop a rigorous framework of building models that process and combine information from multiple modalities.

Deep neural networks (DNNs) have recently emerged as a new tool for understanding the brain, in particular the visual system. These algorithms are inspired by hierarchical models of the visual system, trained on a large set of images, and, under certain circumstances, can achieve human-level performance in object recognition (Krizhevsky, Sutskever, & Hinton, 2012). The same fusion approach described above for fMRI and MEG has been used to relate neuroimaging data to the output of a DNN, finding similarities between earlier layers of the DNN and early visual areas (fMRI) and earlier time points (MEG) and between later layers and more anterior areas of the ventral visual stream and later time points (Cichy, Khosla, Pantazis, Torralba, & Oliva, 2016). While this suggests that there is similarity between the transformations carried out by the ventral stream and a DNN, this correlation does not mean that the underlying processes are identical. Although DNNs are perhaps the best available models of the visual system to date, they are still imperfect models (e.g., not reaching the noise ceiling) and can only go so far in explaining the brain. One important difference is that a DNN is feedforward (unidirectional), while the visual system has both feedforward and feedback connections. Thus, an important next step will be to use recurrent DNNs to see if they provide a more accurate description of brain activity.

Beyond an understanding of what neural measurements represent *biologically*, we must also consider the ecological validity and real-world relevance of these measurements. Contrived task designs (e.g., Gabor patches, visuomotor rotation) are indispensable for understanding low-level neural mechanisms of systems like vision and movement. However, in assuming similar responses across individuals, such tasks may overlook higher-level factors that capture meaningful sources of variability across participants, such as how people naturally view, navigate, or manipulate their environments. Because real-world tasks can be performed in qualitatively different ways, the study of individual variation in naturalistic settings presents an important avenue for future work. Indeed, human neuroscience has begun to utilize naturalistic task designs (Hasson, Nir, Levy, Fuhrmann, & Malach, 2004) and analyze variability in neural synchrony across individuals during naturalistic movie viewing (Parkinson, Kleinbaum, & Wheatley, 2018). Although these types of unconstrained designs present a different set of challenges (in comparison to standardized, well-validated tasks), these findings provide some insight into the neural signals that support complex, real-world behaviors.

Open Questions in Cognitive Neuroscience

Research in cognitive neuroscience distills complex behaviors and mental phenomena into more parsimonious sets of constructs, which can then be measured and manipulated in the laboratory. The hope is that insights from controlled and reduced experiments will translate meaningfully back to the larger phenomena of interest. This leaves room for both conceptual and methodological errors. For example, when investigating phenomena such as concepts, understanding, embodiment, and consciousness, it is critical to clearly state a working definition of the phenomenon. Clarifying our terms enables us to compare findings when we agree on the phenomenon in question and to diagnose terminological disputes or conceptual differences, thereby enabling us to move toward a scientific consensus. Here, we discuss several areas in cognitive neuroscience where progress in scaling up research beyond the laboratory warrants critical examination.

One of these areas is the way that cognitive neuroscience research and the architecture of computational and robotic systems can mutually inform one another. Bridging these fields is far from trivial, given that our understanding of the brain is limited by neuroimaging measures that capture a subset of brain activity over a narrow range of spatiotemporal scales. In addition, experimental constraints make it difficult to measure complex human behaviors, such as communication in natural environments, face processing in real-life crowds, and cognitive/conscious states that are only available through self-report. Incorporating these realistic contexts within cognitive neuroscience research is a critical next step (Schilbach et. al., 2013). We must also consider how neural processing is shaped by evolutionary pressures to socially evaluate individuals along multiple complex dimensions (e.g., social hierarchies). Resulting biases shape our interpersonal interactions, which in turn form many abstract concepts (e.g., religion, philosophy, morality, government). These social processes are unique and fundamental to human survival, but incorporating them within the field of artificial intelligence (AI) will be a considerable challenge.

Part of the problem here is in identifying the cognitive phenomenon of interest. For instance, having a common language benefits communication, but even commonly used words do not contain fixed meanings that are reliably shared across individuals. In fact, in everyday dialogue, the speaker's intention and a sentence's literal meaning often diverge, and words can take on different meanings based on intonation and other subtle contextual cues. Furthermore, a reply can be a response to an utterance occurring at any time along the interaction's trajectory, irrespective of ordering or syntax. These fleeting conceptual dependencies between utterances cannot be easily grasped by simply analyzing long-term, context-free statistical regularities in speech/text, as do the virtual assistants on our smartphones (Stolk, Verhagen, & Toni, 2016). Therefore, theoretical and empirical approaches that respect the core interpersonal and generative nature of human communication are critical for gaining insights into this remarkable ability and for providing a window into understanding alterations of communication in neurological and neurodevelopmental disorders.

Another controversial topic is that of consciousness. Empirical investigations of consciousness examine the neuronal underpinnings of conscious experience and should aim to account for the subjective, phenomenal aspect of *what it is like* to be that organism. Any viable science of consciousness ought to explain not only the conditions under which conscious perception occurs (correlational claim) but also the necessary and sufficient conditions for subjective experience (causal claim). Two common-sense distinctions between different aspects of consciousness are *conscious states*, referring to the level of consciousness or wakefulness (which can range from coma to sleep to the waking state) and *conscious contents*, referring to specific pieces of information that become accessible to awareness (e.g., the experience of pain or the color blue).

Scaling up consciousness science beyond the laboratory faces several challenges. For one thing, operationalizing consciousness is notoriously tricky. We might assume that if a subject can accurately identify a stimulus, the subject is conscious of it. However, the phenomenon of blindsight, whereby individuals with damage to primary visual cortex are capable of making accurate forced-choice discriminations despite reporting no experiences in the affected visual field, illustrates that the identification of a stimulus can occur in the absence of awareness. Uncovering the neural correlates of consciousness is also uniquely challenging. Neural activity seemingly correlated with specific conscious contents may instead simply precede or follow the true neural correlates of consciousness (Aru, Bachmann, Singer, & Melloni, 2012). Lastly, the emphasis on simplified perceptual tasks (e.g., yes/no detection) allows for careful stimulus control and behavioral modeling but may underestimate the richness of consciousness.

Cognition is largely considered to be a process within the brain, but it is important to consider cognition as it emerges from interactions between the brain, body, and environment. James Gibson (1979) proposed that perception is embedded in our experience and that it cannot be fully understood if we overlook our direct interactions with the environment. Daniel Wolpert's research program suggests that the primary function of the brain is action (i.e., enabling movement of the body through the world). These considerations have prompted a "pragmatic turn" toward dynamic and enactive frameworks grounded in sensorimotor processing (Engel, Friston, & Kragic, 2016) and the notion of *embodied cognition*. Embodied approaches recognize that the brain is part of a broader system that developed to engage with the world around us.

Cognition, perception, and action are mental constructs in the human and brain sciences but are more continuous with each other in implementation (Spivey, 2008). Sensory and motor interactions with cognition have been demonstrated in conceptual metaphor, image schema and prototypes, mental rotation, high-level reasoning, language comprehension, memory, and mathematics, to name just a few. In addition, many higher-level processes (e.g., language, arithmetic) appear to involve cortical areas specialized in lower-level processes that are more directly tied to action and space (Anderson, 2014). Thus, considering the complexity of mind-brain-body-environment interactions will be important for future work in cognitive neuroscience.

Putting Science to Work

While cognitive neuroscience continues to yield discoveries into how mental processes relate to brain structure and function, our success at using these discoveries to benefit society has been less inspiring. A predominant factor in this "translation gap" is the scarce communication between researchers and other professional communities, including policy-makers, educators, and clinicians. These divides are maintained by a complex array of factors, such as cumbersome administrative procedures for translational research; priorities in research funding, publishing, and scientific career metrics; and economic pressures, such as demands for clinical revenue.

Despite these limitations, many avenues with potential for translation are being explored. On the clinical front, new developments suggest that a variety of tools may soon be available for therapeutic application. Some of the most promising approaches include neurofeedback (Marzbani, Marateb, & Mansourian, 2016), brain-machine interfaces (Chaudhary, Birbaumer, & Ramos-Murguialday, 2016), sleep-learning paradigms (Arzi et al., 2014), and neurostimulation techniques (Polanía, Nitsche, & Ruff, 2018).

Another aspect of translation is using research to inform policy. In April 2018, the Trump administration enacted a controversial policy that resulted in the separation of over 2,000 children from their caretakers upon entry into the United States. Many members of the scientific community denounced the policy, citing research on the lasting effects of such experiences on children's development (American Psychological Association, 2018; An open letter to Secretary Nielsen, 2018). The *Washington Post* published an op-ed by two researchers asserting that the actions of the government constituted torture (Juvonen & Silvers, 2018). Only after widespread protest did the administration announce an end to the policy. The family separation crisis highlights the need for vigilance against policies that scientific evidence indicates will cause harm. As cognitive neuroscientists, we have a responsibility to apply our expertise to inform policy-makers and the general public, particularly in cases in which the research is clear and the societal costs are high.

In education, research on school start times is an example of translational potential (Wahlstrom, 2016). Studies going back over 20 years show that later school start times benefit teenagers' academic performance and numerous health outcomes, yet fewer than 15% of U.S. high schools have adopted a later start time. Likewise, reading research supports the necessity of explicitly teaching grapheme-phoneme conversion (Rayner, Foorman, Perfetti, Pesetsky, & Seidenberg, 2001), in contrast to competing "global reading" methods that argue for teaching reading through whole words.

These examples illustrate how cognitive neuroscience can have a positive impact on society. Individual scientists can advance translational efforts by initiating dialogues with other professionals to (1) establish relevant questions from the applied perspective, (2) address how basic research can engage these questions, and (3) relay relevant results to the appropriate professional communities. We can also better connect with lay audiences by utilizing alternative forms of scientific communication, such as op-eds, policy briefs, open letters, and social media. As a community we should aim to create more space for translational work in our training programs and conferences. These efforts are gaining support at the national and institutional levels through programs such as the Mind, Brain, and Education Program at Harvard University, the National Center for Advancing Translational Sciences, and the National Institutes of Health Clinical and Translational Science Award program.

Conclusion

As cognitive neuroscientists, we aim to understand the connections among the brain, psychology, behavior, and their implications for society. To achieve our research goals, we must first address the current cultural and ethical issues that impede our progress as a field, including a lack of integrity, accountability, and diversity; researchers must have equal opportunities to pursue their research goals regardless of their gender, race, sexual identity, or socioeconomic status. The growing popularity of open science and preregistration may help to mitigate the current replicability crisis and may additionally improve the culture of science by allowing it to be more accessible. However, incentive systems must follow, and change its reward structure by explicitly rewarding open-science efforts. In addition, while technological advancements and large-scale data sets have allowed us to explore new avenues of research, it is essential to build the methodologies around the research question and not vice versa. Finally, researchers should strive to improve how they communicate their research with the general public. Cognitive neuroscience is a research area that garners much public interest. Therefore, as cognitive neuroscientists, we have a responsibility to publicly and accurately convey the potential implications of our findings and correct misconceptions. Moving forward, honesty, inclusivity, and transparency will promote future scientific developments with the greatest potential to make a positive impact on our health and society.

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