Combining neurophysiological and psychological indicators to understand individual and team cognition and decision-making.

Ruchi Sinha¹, Louise Kyriaki^{1,2}, Zachariah R. Cross², Imogen E. Weigall¹, and Alex Chatburn²

¹ Centre for Workplace Excellence, University of South Australia. 61-68 North Terrace,
Adelaide, South Australia 5000.

² Cognitive and Systems Neuroscience Research Hub, University of South Australia. St
Bernards Road, Magill, South Australia 5072.

Submitted manuscript under review (SMUR)

Abstract

This chapter provides an introduction to neurophysiological methods from the field of cognitive neuroscience, and how they may be applied to address research questions in the field of managerial and organisational cognition. The chapter focuses on electroencephalography (EEG) as an accessible and useful tool to expand the theoretical horizons for research on organisational cognitive neuroscience. We briefly review the cognitive neuroscience methods that have been previously applied to investigate individual and team decision-making and cognition. We then describe contemporary EEG measures that reflect individual cognition and compare them to complementary measures in the field of psychology and management. We also discuss how these neurobiological measures of cognition relate to and may predict both individual cognitive performance and team cognitive performance (decision-making). This chapter aims to assist scholars in the field of managerial and organisational cognition in understanding the complementarity between psychological and neurophysiological methods, and how they may be combined to develop new hypotheses in the intersection of these research fields.

Key words: organisational cognition; cognitive neuroscience; electroencephalography; team dynamics

Introduction

Managerial Organisational Cognition (MOC) is a research field that aims to examine cognition and decision-making processes at the individual and collective levels (Academy of Management Managerial Organisational Cognition (MOC) Division, n.d.; Porac, 2015). Early theorizing by Herbert Simon argued that organisations' decision-making is contingent on how individuals and teams interpret environments, and the cognitive processing behind strategic decisions (Simon, 1955; March & Simon, 1958). Managerial cognition at an individual level is often conceptualized as a set of cognitive processes involving deliberate and/or unconscious computational activities that facilitate decision-making concerning a problem or task (Porac, 2015; Walsh, 1995). On the other hand, team cognition is conceptualized as a collective phenomenon emerging from the interaction between individual cognitive processes, communication, and behavioural coordination (Dunbar et al. 2020; Gorman et al. 2019; Stevens & Galloway 2017).

Recently, there has been a shift towards an interdisciplinary approach to studying cognition and decision-making, with the potential to generate novel insights (Massaro, 2017) by combining perspectives, techniques, concepts, data, and/or theories from cognitive neuroscience with psychology/management science (e.g., Laureiro-Martínez et al., 2015; Senior et al., 2011; Waldman et al., 2017). There is now an "Organisational Neuroscience Division" at the Academy of Management, which seeks to promote and facilitate the integration of neuroscience with management research (Butler & Senior, 2007). Recently, organisational neuroscience scholars have outlined methodological challenges to such an interdisciplinary approach, debating the pros and cons of integrating neuroscience with MOC research (e.g., Healey & Hodgkinson, 2014; Hodgkinson & Healey, 2008; Lindebaum, 2013; McLagan, 2013).

The purpose of this chapter is to outline an interdisciplinary approach to understanding "team cognition" by identifying ways to integrate cognitive neuroscience theory and methods with that from management research. We aim to develop a conceptual framework for understanding the overlap between cognitive neuroscience and MOC research in the conceptualisation and measurement of both individual and team cognition constructs. In one sense, we are developing an initial "integrative dictionary" to identify cognition constructs from management and neuroscience perspectives. We aim to provide readers with conceptual definitions and potential

operationalization of cognition constructs that are often left undefined when scholars consider an interdisciplinary approach. We focus our attention on a particular form of neuroimaging, electroencephalography (EEG), to provide a rich understanding of EEG-based cognition indicators and MOC constructs related to team cognition and decision-making.

Management perspective to individual cognition and team decision-making

In management research, the study of individual-level cognition has focused on the manager's ability to represent knowledge structure and process the available problem information to facilitate decision-making. MOC researchers are keen to examine how individuals develop knowledge structures and if there are trait-like dispositional and predictable differences between managers in how they process and use information from the environment to make effective decision-making. Similarly, management scholars interested in the role of cognition in team decision-making have tried to understand how members with differing cognitive capacities work together to make better decisions. For example, Woolley and colleagues (2007) examined the spatial and object processing cognitive capabilities of members working on a dyadic task. Their works show that collective decision performance is better for dyads in which members' role assignments were congruent with their cognitive capabilities and when dyadic pairs were homogenously high on the same cognitive skill. Further, verbal collaboration benefited dyads where members had roles incongruent with their cognitive skills and were similar in their skills, but adversely affected dyads where members were only adept at one of the two needed cognitive skills (Woolley et al., 2007). This indicates that individual differences in cognitive capacities can help make decisions around selecting and informing team composition and supporting decisions to improve performance. This work was based on self-reported measures of cognitive capabilities and not more nuanced measures of individual cognition. A large body of work in the management field on team decision-making relies on studying the demographic, personality, and skill-based antecedents of cognitive information processing rather than directly studying cognition (Wildman et al., 2014). At the team level, MOC research aggregates self-reported or observed proxies of cognitive capabilities to develop indices of team cognition. Alternatively, the social coordination and communication between members can be used as a proxy to understand how the collective is encoding information, sharing cognitive understanding and how their mental models align towards

shared cognition – as the team makes collective decisions (Cooke & Gorman, 2009; Levine & Zervos, 1993).

The dominant approach in MOC research for the study of individual- and team-level cognition is to experimentally manipulate different forms of information content to track patterns of decision-making behaviours (Walsh, 1995; Wildman et al., 2014). To identify the cognitive steps in information processing leading up to decisions, research often examines the retrospective self-reported description of cognitive knowledge maps; third-party/expert vs. non-expert observation of decision-making behaviour and cognitive mapping, and; the real-time think-aloud method (where managers and teams verbalize the information that captures their attention as they solve tasks; Helfat & Peteraf, 2015; Laureiro Martinez et al., 2009; Ocasio, 2011). These methods have provided us with critical insights into how individuals and teams might attend to and process information consciously (Helfat & Peteraf, 2015; Ocasio, 2011). At the same time, MOC scholars note methodological limitations concerning inferred cognition constructs' validity and reliability – especially due to the role of social desirability and biases emerging from memory (Lipshitz & Bar-Ilan, 1996). Limitations are also noted with the over-reliance on the assumption that cognition structures and processes can be understood through inferences made from observed behaviour (Galotti et al., 2014). The solution to these limitations may lie in adopting a multidisciplinary approach that relies not only on sophisticated behavioural methodologies but also on brain imaging techniques to understand cognitive computations during complex decision-making. This is where cognitive neuroscience can provide novel insights by capturing the often subconscious cognitive processes, including the temporal sequence of how and when the brain encodes information from its environment (Laureiro-Martinez, 2017) – thereby providing new perspectives to understanding both individual and team cognition.

The cognitive neuroscience perspective of individual cognition and team decision-making

As a field, cognitive neuroscience emerged from the integration of the cognitive sciences, psychology, neurobiology, neuroscience, and computational modelling (Posner & DiGirolamo, 2000). Cognitive neuroscience focuses on examining neural processes that underlie cognition and behaviour, with EEG (as an example of one brain imaging technique) used to study neural electrical activity and brain processing as early as the 1920s (Berger, 1929; Ince et al., 2020). This

field directly observes the neurophysiological activity underlying cognition. These cognitive processes are both conscious and unconscious to the individual or team. Compared to MOC, cognitive neuroscience research is far more descriptive, providing rich data on both trait-like brain capacities and transient states of brain function during a particular event or task (Debener et al., 2006). For example, in a novel use of EEG in a classroom context, scholars have shown that when individuals have synchronized brain activity (neural coherence), there is greater shared attention and better engagement and social dynamics (Dikker et al., 2017). In summary, cognitive neuroscience attempts to explain the biological basis of cognition and decision-making, and this can add to our observations and understanding of individual and team-based decision behaviours (Decety and Grezes, 2006).

Cognitive neuroscience techniques and methods provide various benefits to understand individual and team cognition and decision-making. For example, brain activity measures offer spatiotemporally precise characterizations of cognitive constructs such as attention, perception, and task switching (Waldman and Hannah, 2015; Waldman & Balthazard, 2015). Many of the cognitive processes captured by EEG are unconscious, thus when combined with MOC self-report measures, can reduce retrospective and faking biases while providing data on the temporal attentional processes leading up to coordination and decision-making. Cognitive neuroscience can also clarify the ontological basis of some abstractly defined cognition constructs in the MOC field, allowing scholars to develop greater discriminant validity for similar psychological constructs (Powell, 2011). The cognitive theories emerging from neuroscience and the biologically based measurements using EEG can improve the understanding of MOC research constructs by allowing scholars to triangulate data, to develop new theories and test hypotheses (Healey and Hodgkinson 2014; Senior et al. 2011).

Cognitive neuroscience can also offer neurobiologically-informed models of human cognition and behaviour. One such model, currently prevalent in the cognitive neuroscience literature, is predictive coding (Friston, 2010; Huang & Rao, 2011). While mathematically complex (Friston, 2010; Bastos et al., 2012), the core concept underlying the approach is simple: the brain constructs internal models (similar in concept to schemata) of the environment and actively tests these against incoming sensory stimuli. In other words, the brain does not see; it predicts what it sees and tests it to determine if the prediction is true or false. When the sensory

information from the environment and the predicted internal model do not match, there is a prediction error (Friston, 2010). This prediction error itself is a surprise and thus acts as a signal for the human brain to engage in model updating (Friston, 2010). For example, individuals update their memories preferentially in situations where incoming information shows that their predictions are not upheld (Rouhani et al., 2018, 2020). Similarly, when individuals encounter unexpected words in a sentence (e.g., “The sandwich devoured the hungry boys”), EEG-based markers of cognition (e.g., event-related potentials) can indicate surprise and internal model updating (Bornkessel-Schlesewsky & Schlewsky, 2019; Kyriaki et al., 2020). While predictive coding is well-established in cognitive neuroscience as an explanatory model underlying a great amount of cognitive and behavioural processes, there has been relatively little work that has attempted to relate these processes to team-level cognition or functional outcomes. How predictive processes relate to (for example) establishing shared mental models to facilitate or inhibit team cohesion are open questions for future research.

A plurality of perspectives: Adopting an interdisciplinary perspective and some caveats

There is no doubt that managerial cognition studies can benefit from an interdisciplinary lens combining data, methodology, and concepts from cognitive neuroscience (Senior et al., 2011). However, interdisciplinary research comes with its own set of challenges, including differences in the terminology and labelling of constructs. Neuroscience focuses on neural connections and cognition-related neural markers to understand how individuals attend, code, retrieve, and process information while making decisions. Such directly measured, neurobiological markers underlying cognition may not easily map onto cognition constructs typically studied in management and organisational cognition area. In this chapter, we endeavour to highlight the overlapping and complementary aspects of adopting a multidisciplinary lens to examining individual and team decision-making.

It is critical to remind MOC scholars of the general tendency to view biological and physiological indicators of human behaviour as more “real” than the psychological perceptions of internal cognitive milieu (cf. Niv, 2020). Ashkanasy and colleagues (2014) decry excessive excitement at seeing neuroscientific studies as the saviour for the field of MOC (see also Cropanzano & Becker, 2013; Ringleb & Rock, 2008). This often misplaced excitement can result

in scholars replacing self-reports and behavioural observation methods with only neuroimaging cognition measures, which are thought to be “more objective measures” (Lindebaum, 2013; McLagan, 2013). However, such reductionism is not preferred and is not in line with current cognitive neuroscience theory. Observation of neural activity is not meant to perfectly map onto a single cognitive process or behavioural indicator of decision-making (Lindquist et al., 2012). It is thus recommended that future MOC research that seeks to adopt neuroscientific frameworks should continue to focus on multivariate measurement of constructs of interest. We encourage scholars to actively disengage from reductionist thinking and salesmanship of a particular disciplinary perspective, as human decision-making is a complex phenomenon that emerges from the interaction between the neurobiological, perceptual and social world in which individuals and teams are embedded.

Why EEG? An appropriate and accessible method for identifying neurobiological indicators of cognition

Neuroscience is a rapidly evolving scientific field, with various neuroimaging methods shedding light on the neurobiological underpinnings of decision-making (Balleine, 2007; Heekeren et al., 2008). Electroencephalography (EEG) is one such method of neuroimaging that captures the communication between neuronal networks of the brain with unparalleled temporal precision (Luck, 2014). Recording EEG activity from the human brain involves placing electrodes (small recording disks) at standardised positions on the scalp, usually embedded within an elasticated cap (Avidan & Sleigh, 2019), as shown in Figure 1.

Figure 1. Example of an EEG set-up and recording during an in-lab computerized task.

EEG records the brain's electrical activity, and the main neural signal captured is that of rhythmic changes in pyramidal neurons (the primary input-output cells of the cortex; Luck, 2014). The communication between neural networks is rapid and complex, occurring on a millisecond-by-millisecond timescale across spatially distant regions in the brain (Bornkessel-Schlesewsky et al., 2016; Marois & Ivanoff, 2005). As such, EEG can be used to connect outward human decision-making behaviours to neural firing within the brain across different stages of information processing. EEG's ability to capture neural activity with fine-grained timing is an advantage over other techniques such as functional magnetic resonance imaging (fMRI). While fMRI can identify neuroanatomical correlates (i.e., specific brain regions with increased activity) in relation to a behaviour, the timescale is significantly slower (seconds, rather than milliseconds; Laureiro-Martinez, 2017, see Massaro 2017 for a comparison of neuroscientific methods and their application to MOC research).

Recently, MOC scholars have begun to explore EEG-based methodologies, with several suppliers of EEG systems providing accessible and affordable experimental equipment (e.g., Balthazard, Waldman, Thatcher, & Hannah, 2012; Hannah et al., 2013; Waldman et al., 2011a). EEG recording systems are significantly cheaper than fMRI-based methodologies (~\$40,000 versus > \$1 million, respectively; Massaro, 2017) and have far lower operational and maintenance costs. Wireless, light-weight and portable EEG headsets can be used in naturalistic environments with little obtrusion and high ecological validity, allowing participants to traverse complex environments and interact in team scenarios, as opposed to completing lab-based tasks in

stationary positions (e.g., while lying motionless in an fMRI scanner; Hedgcock & Rao, 2009). Further, due to both the cost feasibility and the portability of EEG, researchers can conduct studies with larger samples - something that has been a limitation in most fMRI research in the area of management (Waldman et al., 2017).

EEG-based measures of human cognition

To appreciate the utility of using EEG to study team cognition and decision-making, it is essential to understand the definitions and nature of key EEG markers and how they relate to individual cognition constructs. From this understanding, one can then develop a broad sense of how individual-level EEG markers inform cognition at the team level. To support this understanding, we have developed a glossary of terms that will help readers from this point forward to interpret the neuroscience concepts and technical terminology (see glossary box below). While this chapter is not meant to provide technical training in EEG measurement and analysis, it aims to serve as a starter for those scholars interested in pursuing this interdisciplinary examination line. For those interested in learning the specific steps for EEG data analysis (beyond the scope of this discussion), see Luck (2014) for an introduction to the recording and analysis of EEG data in general (including the measure of “event-related potentials”), and see Klimesch (1999) for an introduction to oscillatory dynamics in the human brain and how they relate to behaviour and cognition.

Neuroscience glossary box

Aperiodic component: A measure derived from electroencephalography (EEG) data, thought to reflect “neural noise,” and quantified as a negative slope in EEG power. A flatter slope is thought to reflect the decoupling of neural networks. This measure varies as a function of age, health, and states of consciousness (e.g., awake or asleep).

Cross-frequency coupling (CFC): The relationship between two oscillations occurring at different frequencies in the electrical activity of the brain. Quantifications of this measure show that the phase of “slow” oscillations (e.g., slower than 3 Hz, or 3 cycles per second) predict the size/amplitude of “faster” oscillations (e.g., faster than 8 Hz) in the brain.

EEG-Engagement (EEG-E): An individual-level measure derived from the human electroencephalogram is computed by modelling the participant’s neural activity’s voltage power. Higher levels of EEG-Engagement are proposed to positively correlate with higher levels of attention, task demand, and/or cognitive demand.

EEG-Workload (EEG-WL): An individual-level measure derived from the human electroencephalogram is computed by modelling the participant’s neural activity’s voltage power. Increased levels of EEG-Workload are proposed to positively correlate with higher levels of executive function, task demand, and working memory load arising from complex cognitive tasks.

Electroencephalography (EEG): The measurement of electrical activity (known as the electroencephalogram) from the brain. This measurement is attained by placing recording disks (electrodes) on the scalp, amplifying the electrical signal, and plotting electrical voltage changes over time. Within the EEG signal, sources of neural activity can be extracted, which are associated with cognitive, sensory, or motor events.

Event-related potential (ERP): An electrical potential within the electroencephalogram, related to specific events (e.g., specific cognitive responses or experiences). The event-related potential is computed by averaging the electroencephalogram over multiple events or experimental trials.

Frequency band(s): The frequency of ongoing EEG activity is typically categorized into five canonical bands split by frequency levels. Each band is classified as a range of Hz, where 1 Hz represents 1 cycle per second. These bands are delta (~ 1 – 3.5 Hz), theta (~ 4 – 7 Hz), alpha (~ 8 – 13 Hz), beta (~ 13 – 30 Hz) and gamma (> 30 Hz). Changes in these bands, such as differing timing of the brain activity, or the relative size/amplitude of the activity, correlate with many aspects of cognition.

Neural oscillations: Human brain activity is dominated by rhythms that occur at different frequencies, which reflect changes in the excitability of groups of neurons. An increase in the excitability of such groups of neurons can occur in different areas of the brain and can vary in size/amplitude (typically quantified in microvolts; μV), time (occurring across milliseconds to seconds), and frequency (ranging from slow, i.e., < 1 Hz, to fast, i.e., > 100 Hz).

Neural phase: The phase of an oscillation in the EEG activity reflects the state of the voltage of a population of neurons in the brain. The neural phase can be in either a “lower” or “higher” state. The neural phase is associated with perceptual processing, such that if an oscillation at around 10 Hz is in the “lower” phase before a brief flash of light is shown, this flash is more likely to be perceived by a participant than if the oscillation was in the “higher” phase.

Neurophysiologic Synchronies (NS): A group- or team-level measure calculated by combining members’ EEG-Engagement and/or EEG-Workload. Increased levels of Neurophysiologic Synchronies are thought to reflect how synchronized the team is as a whole and positively correlates with higher team performance on a task (Stevens & Galloway, 2017).

Power spectral density (PSD): Reflects the magnitude or strength of activity in a given frequency band. Levels of PSD correlate with cognitive processes such as visual attention (e.g., a decrease in this measure can be correlated with greater visual attention).

Theta oscillations: A measure arising from EEG activity, theta oscillations generally occur at a frequency of 4 – 7 Hz. Thought to be generated in hippocampal structures deep in the brain, theta oscillations play a crucial role in memory and cognitive control.

The current state of the interdisciplinary field: Model-derived EEG measures

An emerging body of research has examined individual and group-level EEG-markers of managerial and team cognition (e.g. Berka et al., 2004; Kolm et al., 2013; Stevens et al., 2009; Stevens & Galloway, 2019). These measures of EEG activity have been used to quantify aspects of individual and team cognition. They are computed from activity in different frequency bands (i.e., delta, theta, alpha, beta, and gamma; Berka et al., 2007; Prinzl et al., 2000, 2003; Stevens & Galloway, 2019). This existing research has developed EEG-based measures at both the individual and team levels (Gorman et al., 2019) to provide insight into aspects of cognitive processing and will be introduced below. However, these measures are not typically considered or used in the general cognitive neuroscience field. Following a brief overview of the previous literature, we will introduce contemporary EEG-based markers of cognition that may be applied to individual and team cognition.

Individual-level EEG measures related to cognition: Past research at the intersection of management and neuroscience has relied heavily on two EEG-derived measures at the individual level: 1) EEG-Engagement (EEG-E) and 2) EEG-Workload (EEG-WL; (Berka et al., 2004, 2007). EEG-E is thought to reflect the level and complexity of cognitive processing, allocation of attentional resources, and task demand. For example, a team's appointed leader shows higher EEG-E than other group members, indicating higher levels of task demand and engagement of more significant attentional resources compared to the other team members (Kolm et al., 2013). EEG-WL is thought to reflect the level of executive function, task demand, and relative working memory load (i.e., increases in short-term memory requirements during a complex cognitive task) (Berka et al., 2007). For example, when working in a group, EEG-WL is higher than working alone and is also higher when providing instructions than following instructions (Stevens, Galloway, Campbell, et al., 2013; Stevens, Galloway, Wang, et al., 2013). Both EEG-E and EEG-WL can be measured over time, with changes (e.g., higher or lower levels) reflecting individual cognitive processes (Berka et al., 2004, 2007). Each of these measures is derived from an individual's brain activity. The absolute and relative power of individual neural activity is modelled using classifier models (e.g., artificial neural networks, for review, see (Berka et al., 2007). Researchers using these EEG-derived measures propose that EEG-E and EEG-WL can operate together depending

on the task environment, the level of task demand, and the effort required by the individual to complete the task (Berka et al., 2007).

In another recent study combining EEG markers of high-level cognitive functions with self-reported leadership measures, Balthazard et al. (2012) differentiated transformational and non-transformational leaders based on EEG power spectral analysis variables in both civilian and military leaders. This research suggests a strong correlation between psychometric measures of transformational leadership (MLQ) and a range of EEG measures (Balthazard et al., 2012). Their findings suggest a dominant role of frontal brain activity for informing predictions of transformational leadership qualities in an individual (Balthazard et al., 2012). Contrasting the brain activity in the two hemispheres of the brain, transformational leaders exhibited less connectivity (more differentiation) in the left hemisphere and more connectivity (more integration) in the right hemisphere (Balthazard et al., 2012). This literature suggests that many EEG-based markers are useful additions to psychometric testing to identify individual qualities such as transformational leadership. On the whole, there is a small body of emerging work that is beginning to look at EEG-based markers to understand how individual cognitive capacities relate to individual decision-making and behaviours in the workplace.

Team-level EEG measures of cognition: Interdisciplinary research on team cognition that combines EEG markers and behavioural measures is scant. The existing work comes primarily from a small group of researchers who are affiliated with the UCLA Brain Research Institute (cf. Ronald H. Stevens) and have links to a company called “The Learning Chameleon” (<http://www.teamneurodynamics.com/>). The body of work emerging from this group typically combine every team member’s EEG-E and/or EEG-WL to develop a team-level measure of shared cognition – also termed Neurophysiologic Synchronies (NS). Neurophysiologic Synchronies represent the synchrony or similarity between team members on EEG-E and EEG-WL (Stevens, Galloway, Wang, et al., 2013). The higher the NS, the more synchronised a team’s neural activity is, and NS is found to positively correlate with high teamwork and/or communication demands (Stevens & Galloway, 2017). For example, research shows that High NS is observed during briefing and debriefing stages, as well as during important or stressful events, where all members are actively participating and communicating (Stevens et al., 2014). During a task, NS is most consistent and high when strong leaders and decisive language are

used. It varies more with low leadership presence, low task awareness, and informal commands (Lamb et al., 2014; Stevens et al., 2014). However, flexibility in team NS is also important, as effective teams likely do not require high neural synchrony levels for the duration of a teamwork exercise to complete relatively simple or routine tasks (Lamb et al., 2014).

More recent work using less computationally intense metrics and that are more aligned with well-studied EEG metrics have also examined how patterns of neural activity synchronize between members of a team (Bevilacqua et al., 2019; Dikker et al., 2017; Reinero et al., 2020; see Figure 2 for a graphic representation of what brain-to-brain synchrony might mean in the context of teams). For example, Bevilacqua et al. (2019) revealed that students who reported greater social closeness to their teacher showed higher brain-to-brain synchrony with the teacher, and this predicted cognitive learning outcomes. Similar work (e.g., Davidesco & Milne, 2019) has found that student-to-teacher brain synchrony predicted learning in a sequential manner, predominantly in the alpha band.

Figure 2. Schematic of how EEG team synchrony is typically studied by researchers. (A) Two teams each comprised of three individuals listen to a workplace audio brief while their EEG is recorded (adapted with permission from Bevilacqua et al., 2019). Graphic representation of low (B) versus high (C) team synchrony from the raw EEG trace during task engagement. (D) and (E) illustrate the EEG signal between the low and highly synchronized teams, respectively, once the raw EEG has been processed. (F) Schematic illustration of the correlation between team EEG synchronization (represented on the y-axis; higher values denote higher team synchrony) and behavioural performance (e.g., memory of the audio brief, represented on the x-axis).

Another study (Dikker et al., 2019) found that pairs of individuals' trait empathy, social closeness, engagement, and social behaviour (e.g., joint action and eye contact) predicted the

extent to which their brain activity became synchronized, most prominently in the low alpha (~ 7-10 Hz) and beta frequencies (~ 20-22 Hz). Together, these studies suggest that brain-to-brain synchrony in dyads and teams predicts essential cognitive and social outcomes (e.g., memory, engagement) over and above intra-individual cognition measures (e.g., EEG-based markers of one person predicting the outcome). From this perspective, brain-to-brain synchrony measures may also be applied to research on team performance in managerial settings, offering novel insights into how information is shared between team members, how this manifests neurally, and how this predicts behavioural outcomes.

While the studies discussed above have shed light on the neurophysiological mechanisms underlying team-related behaviours, the basic neuroscientific literature has primarily focused on cognition at the individual level, with little known regarding how established neurocognition metrics relate to the neurophysiology of teamwork. Further, the EEG-based measures such as EEG-E and EEG-WL are developed using complex computational models and do not clearly correspond to other prominent cognition measures used in the cognitive neuroscience field. A challenge to using these aforementioned measures to explain the neurodynamics of team cognition is that the resultant aggregated team cognition measures are not as well-grounded in basic neurophysiological principles dominantly accepted in the field of cognitive neuroscience. The next section introduces an integrative dictionary that seeks to discuss the overlap between management cognition constructs and the EEG-based markers of aligned cognition.

Integrative dictionary for commonly studied management cognition constructs and EEG-based cognition constructs

In reviewing the relatively limited interdisciplinary EEG-based research on individual and team cognition, there is a lack of consistency in which cognitive constructs are being theoretically proposed and measured using EEG. This section seeks to develop a dictionary that allows readers to interpret the overlaps between cognition constructs typically studied in management research and the EEG-based markers of those cognitive concepts in the neuroscience literature. Such a discussion is likely to help future management scholars identify whether EEG markers are a relevant alternative approach to use as they answer various key MOC research questions. Similarly, such a dictionary can help cognitive neuroscience researchers consider behavioural and perceptual measures of cognition and team level constructs as they design their studies. While

there is a significantly extensive range of markers for cognition that may be recorded and analyzed using EEG data, here we focus on the EEG markers that overlap with cognition constructs typically discussed and studied in the MOC field.

Cognitive readiness. In the field of managerial cognition, scholars often refer to an individual's level of readiness in terms of their preparedness and alertness to external stimuli or information. Readiness is considered to be related to selective attention, which is defined as the automatic or intentional process directing awareness toward selective stimuli or responses in the environment to exclude irrelevant others (Ocasio, 2011). Management research typically refers to this process but empirical work directly measuring this cognitive construct is limited – with only a handful of studies relying on surveys and frequency analysis of document reviews (Ocasio, 2011).

Neurobiologically, “cognitive readiness” or “alertness” is reflected in fluctuations in intrinsic neural networks (Sadaghiani & Kleinschmidt, 2016), differences in pre-stimulus neural activity (i.e., neural activity before stimulus onset; Min & Park, 2010), and the excitability of neural populations, which can be quantified by measuring changes in the power and phase of alpha oscillations (~ 7 – 13 Hz). According to a model proposed by Sadaghiani & Kleinschmidt (2016), cognitive alertness is linked to EEG markers that capture the widespread increase in alpha power (i.e., across the scalp), while cognitive readiness is associated with the phase of alpha oscillations, which predicts whether incoming sensory information will be efficiently processed.

Attentional control and allocation of cognitive resources. In MOC research, the construct of attentional control is discussed as a higher-order cognitive step captured by understanding how individuals direct/refocus their attention toward selective aspects of the environment relative to an internal goal (Laureiro-Martínez et al., 2015). Typically, in the MOC field, attention is studied by varying the salience of stimuli and/or manipulating participants' ability to attend to relevant sensory information. Then researchers analyze the participant's think-aloud verbal data by looking at the tone, speed, the number of pauses, and words used. Subjective rating measures of attention and the Flanker task have also been utilized in the literature to measure attentional control (Laureiro-Martinez, 2017; Ocasio, 2011).

From a neurobiological perspective, attention can be viewed as the brain's ability to efficiently process incoming sensory input, often prioritizing salient or task-relevant information. Seminal work by Klimesch (e.g., Klimesch, 2012; Klimesch et al., 2007) demonstrates that alpha

oscillations are tightly linked to attentional control. In the EEG, alpha oscillations are argued to reflect two fundamental functions of attention (1) by acting as a filter, such that alpha oscillations actively suppress task-irrelevant brain networks (reflected in an increase in alpha power) and excite task-relevant areas (reflected in a decrease in alpha power), and; (2) facilitate controlled access to stored information (e.g., from long-term memory) during the processing of sensory input that varies in semantic complexity¹.

Cognitive flexibility. In MOC research, an individual's cognitive flexibility is linked to decision-making performance on tasks (Laureiro-Martínez & Brusoni, 2018). Cognitive flexibility as a construct captures the ability to adapt mental processes to a given problem- such that the person can switch between habitual vs. deliberative modes of decision-making. The habitual decision mode is associated with fast, automatic processing based on habits. In contrast, the deliberate decision mode facilitates a 'slow,' controlled exploration of new courses of action. Managers with high cognitive flexibility are more likely to use habitual processing in a well-structured task and deliberate/controlled processing in an ill-structured task (Laureiro-Martínez & Brusoni, 2018). Typically, cognitive flexibility is measured using self-report psychometric scales or on tasks such as the Stroop Task and Wisconsin Card Sorting Task (Laureiro Martinez et al., 2009).

In neuroscience, cognitive flexibility is a higher-order concept related to executive control, likely emerging from neural activity in the prefrontal cortex (Knight et al., 1995, 1999; Miller, 2000). Several EEG-based oscillatory dynamics have been shown to reflect cortical computations of prefrontal driven executive control (for review, see Helfrich & Knight, 2016). These include phase resetting of endogenous oscillatory activity, such that the phase resetting of low-frequency activity in response to task-relevant input predicts behavioural changes (Daitch et al., 2013; Sweeney-Reed et al., 2015; Voloh et al., 2015). From this perspective, phase resetting is argued to facilitate cognitive flexibility by aligning activity in widespread cortical regions. Similarly, cross-frequency coupling (CFC) has also been proposed as a candidate mechanism for executive control and cognitive flexibility by coordinating information transfer between spatiotemporally organised neural networks (Helfrich & Knight, 2016). CFC refers to the coupling between different

¹¹ Please note that we do not argue that activity in the alpha band is the only EEG-based measure of attention (for an ERP-based summary of neurophysiological correlates of attention, see (Luck et al., 2000) and (Woodman, 2010); however, given the scope of this chapter, we focus on well-known oscillatory correlates of cognition.

oscillatory frequencies, whereby the phase of slow oscillations (e.g., < 8 Hz) modulates the amplitude of higher frequency activity (e.g., > 50 Hz). CFC has been shown to facilitate information transfer and integration across different brain region (Sweeney-Reed et al., 2015; von Nicolai et al., 2014). Finally, the power (i.e., amplitude) in specific frequency bands (e.g., 4 – 7 Hz) is related to cognitive flexibility. For example, compared to healthy controls, children with Autism Spectrum Disorder demonstrate deficits in the power of frontal theta oscillations (i.e., from anterior electrodes) during a computerised version of the Wisconsin Card Sorting Test (Yeung et al., 2016).

Shared team cognition. In the MOC field, shared cognition at a collective level is typically conceptualized and measured through the construct of shared mental models (SMM), which refers to the collective understanding of common team knowledge (Waldman et al., 2015). Team knowledge is often referred to as common and overlapping memory of knowledge or knowledge distribution relative to a member's role or expertise (Cooke et al., 2000; Klimoski & Mohammed, 1994). High similarity of mental models between team members is suggested to lead to effective team performance (Cooke et al., 2004; Waldman et al., 2015). When knowledge is uniquely distributed among team members, MOC research typically examines the construct of team coordination as a close antecedent to the development of shared cognition. Coordination is then the team's ability to compensate and exploit variabilities in team members' behaviour and knowledge to aid decision-making. For example, team coordination is measured by observing behavioural communication (frequency and evenness) as members adapt and integrate actions, knowledge, and other members' goals. Typically, shared team cognition is measured through coding of observation by subject-matter experts or through use of retrospective self-reported survey items. Similarly, Shared Team Mental Models or Shared Team Cognition is derived through aggregating behavioural observations of team communication and/or by seeing the overlap in data from think-aloud protocols, interviews, diagramming, think verbal troubleshooting and pathfinder networks (DeChurch & Mesmer-Magnus, 2010; Langan-Fox et al., 2000; Mohammed et al., 2010).

In neuroscience, research on shared cognition among dyads and small groups is captured by aggregating individual member's EEG-WL spectral analysis data (Waldman et al., 2015) - wherein EEG-WL is a marker of the cognitive processing required to gather information and compare it to internal mental models. More recent work on neurophysiologic synchronies have

now begun to capture the overlap in neural activity among multiple members in a team to capture how much overlap or difference there is in how members pay attention to, react, and process common information (Barraza et al., 2020; Dodel et al., 2020; Stevens et al., 2014, 2017).

Following this connection of management cognition constructs and EEG-based markers of aligned cognition, we now turn to newer developments in cognitive neuroscience methods and discuss MOC research applications. In the future avenues of research section below, we will provide a basic understanding of the neural correlates of relevant cognitive processes that we believe are crucial to drawing inferences about individual and team cognition.

Future avenues for interdisciplinary research on team cognition

Here, we introduce two neurobiological EEG-based markers associated with various aspects of cognition, the individual alpha frequency (IAF) and the aperiodic $1/f$ exponent, and generate novel hypotheses about how these markers may relate to team cognition and decision-making. While IAF and the $1/f$ exponent (albeit far less) have been related to individual differences in intelligence, processing speed, and memory, they differ significantly from what has been typically studied in the organisational neuroscience research on individual and team cognition, which is often quantified using EEG-E (Engagement) and EEG-EL (Workload).

A central tenet of cognitive neuroscience is to characterize how the brain processes sensory information and constructs a cognitive and perceptual world. Many modern theories of human neurobiology and cognition are centered on principles of hierarchical predictive coding (Friston, 2010; Huang & Rao, 2011). From a predictive-coding-based view, the brain serves to gather information from its surroundings to test hypotheses or beliefs about its current internal representation of the world (Alamia & VanRullen, 2019; Arnal & Giraud, 2012; Bastos et al., 2012; 2020; Friston et al., 2012). Prediction errors occur when expectations (i.e., top-down predictions) of the world do not match actual (bottom-up) sensory input, allowing the brain to update its internal model. As discussed earlier, predictive-coding-based views of the brain have been used to explain many cognitive processes, including attention (Spratling, 2008; Summerfield & Egner, 2009), visual processing (Feuerriegel et al., 2018), and language (Bornkessel-Schlesewsky & Schlewsky, 2019; Lewis & Bastiaansen, 2015). Given its prominence in contemporary cognitive neuroscience theories, we now attempt to link a predictive-coding-based

view of the brain to MOC-based constructs, using EEG-derived neural oscillatory activity as a case-in-point.

Neuronal oscillations as endogenous markers of human cognition

Neuroscientific research typically focuses on either task-related or resting state measures of brain activity (for a schematic of the many ways of analyzing task- and resting-state EEG, see Figure 3; (Klimesch, 1999). The former's benefit is that it involves direct measurement of brain activity related to a behavioural or cognitive operation (Luck, 2014). The latter's benefit is that it relates to trait-like factors present in the workings of the individual's brain (Bornkessel-Schlesewsky et al., 2015). In the following, we discuss two prominent resting-state brain activity measures of relevance when combining approaches from the neuroscientific and MOC disciplines. These two trait-like neurocognitive markers are a) individual alpha frequency (IAF; Corcoran et al., 2018; Klimesch, 1999) and b) the $1/f$ exponent (Donoghue et al., 2020; Voytek et al., 2015).

Figure 3. Schematic and examples of the many ways task-related and resting-state EEG are typically quantified and used to predict cognition and behaviour. (A) Raw EEG trace taken from ten seconds of a resting-state eyes closed recording. Each horizontal line represents the electrical activity recorded from a single channel placed on the scalp. (B) Raw EEG trace taken from ten seconds of a task-related EEG recording during a sentence processing paradigm. During this period, the participant was presented with the sentence *the sandwich devoured the boy* and was required to judge the sentence's grammaticality. The solid vertical lines correspond to each word's presentation in the sentence,

the timing of which can be used during offline processing to extract EEG surrounding the presentation of the critical word (coded in red). (C) After pre-processing the raw EEG from (A) and (B), you can clearly differentiate the ongoing EEG into the canonical frequency bands. Note the differences in frequency (Hz; cycles per second) and amplitude between delta and beta activity during the ten-second period. (D) Power spectral density (PSD) plot estimated from a two minutes eyes closed resting-state EEG recording. Frequency (Hz) is represented on the x-axis (values from left to right indicate low to higher frequencies). Power is represented on the y-axis (higher values indicate a greater concentration of power). Note the clear spectral peak in the alpha range, which reflects this participant's individual alpha frequency. (E) PSD plot showing the aperiodic or $1/f$ slope extracted from the same resting-state recording as (D). As is characteristic of aperiodic "background" neural activity, note that there is a greater concentration of power in the lower frequency range (e.g., < 10 Hz), with power decreasing as frequency increases. (F) Schematic of the ongoing phase of neural oscillations and perception of incoming sensory information. Note that the words *sandwich* and *devoured* occur during the negative phase of this ongoing oscillation. (G) Event-related potential (ERP) during the presentation of the critical word *devoured*. This ERP represents the aggregated neural response at the equivalent time point of the sentence across multiple sentences and multiple participants. (H) schematic of how different EEG patterns interact, such as through cross-frequency coupling (CFC). Here, the spindle (the short occurring burst of activity) occurs during the up-state (i.e., positive deflection) of the slow oscillation. (I) Comodulagram illustrating the pattern of activity shown in (H). Here, warmer colors indicate an increase in frequency activity, with the phase of the slow frequency (roughly at 1 Hz; represented on the x-axis) being associated with an increase in the amplitude of frequency activity at roughly 12.5 Hz (shown on the y-axis). Note that all data visualized in this figure are derived from a single participant's EEG recorded in our laboratory, except for (G), which is averaged across a group of participants.

IAF as a neural marker of inter-individual differences in information processing

Neurobiologically, IAF reflects the prominent spectral peak (i.e., the concentration of electrical power) within the canonical alpha boundary ($\sim 7 - 13$ Hz). IAF is argued to indicate the speed of electrical information transfer in the brain and has been related to behavioural and cognitive outcomes. For instance, IAF positively relates to measures of working memory, attention, and general intelligence (Corcoran et al., 2018; Cross, Santamaria, et al., 2020). Differences in processing speed between high and low IAF individuals have also been shown to modulate elements of memory consolidation wherein neural connections that form memories become more stable during sleep (Cross et al., 2020). Higher IAF is also linked to temporal (i.e., time-based) precision of perception. Higher IAF individuals actively sample visual sensory information faster than lower IAF individuals (Samaha & Postle, 2015). A higher-order perspective on these collated data is that differences in IAF may relate to individual differences in the speed at which internal representations of the world are updated, with higher IAF individuals more rapidly updating internal-based models of the world in comparison to lower IAF individuals (e.g., Bornkessel-Schlesewsky, 2015).

Although IAF has not been explicitly related to common MOC constructs, the posited trait-like differences in IAF and how these determine the information processing style of the individual (with high IAF relating to faster and more liberal updating of internal models and lower IAF

relating to slower and more conservative updating of internal models; Bornkessel-Schlesewsky et al., 2015), allows for several possibilities to be explored in terms of both cognitive flexibility and readiness. Both high and low trait IAF scores may relate to the successful use of cognitive flexibility; it could be expected that high IAF values would predispose an individual to faster formation of habitual processing, through more liberal model updating, and thereby a greater facility towards deliberative processing in unfamiliar situations. A lower IAF individual may preferentially conserve an established, habitual processing mode, even when working on an unfamiliar task. Similarly, in terms of cognitive readiness, it may be that higher levels of environmental sampling and model updating would lead an individual with a higher IAF value to greater preparedness to accept incoming information, but less ability to selectively ignore irrelevant data amongst this, in comparison to a lower IAF individual.

Whether and how IAF may relate to team dynamics has yet to be established in the neuroscientific or organisational neuroscience literature. There is no empirical data yet on how such trait-like cognitive capacities can impact individual and team performance. There are several avenues for future research here, which would be mutually beneficial to both neuroscience and MOC. For instance, scholars could look at the impact on team performance of teams with heterogeneous versus homogenous IAF member profiles. Similarly, team composition on neuro markers can be used to understand the development of shared mental models, social facilitation, collaborative learning and coordinated action. Looking at members' IAF and how they interactively influence shared attention and cognition through inter-brain connectivity to effect team decision performance would be of particular interest. Another area worthy of future research would be to explore how a team composed of a high IAF leader and lower IAF members is equally efficient in obtaining desired outcomes than other team compositions.

Aperiodic exponent of the EEG and individual differences in "neural noise"

As well as showing transient oscillatory activity (e.g., in the alpha band), the electrical activity recorded from the brain also displays a dominant $1/f$ -like spectral pattern (simply put, that power decreases with increasing frequency; Donoghue et al., 2020; He, 2014; Lendner et al., 2020). The $1/f$ pattern of the EEG is thought to index "neural noise" (Voytek et al., 2015), such that a flatter slope may reflect less efficient communication between intrinsic and task-related

neural networks, which has been proposed to be a candidate mechanism underlying phenomena such as age-related reductions in cognition (Voytek et al., 2015).

In the healthy brain, aperiodic activity has been implicated in a variety of higher-order cognitive computations (Fellner et al., 2019), partially explaining individual differences in memory (Sheehan et al., 2018), processing speed (Ouyang et al., 2020) and predictive processing in language (Dave et al., 2018). The slope of the $1/f$ power distribution also varies parametrically by task difficulty: it is at its steepest for easy tasks and becomes progressively shallower with increasing task difficulty (He et al., 2010). In this way, aperiodic activity may serve as a proxy for inter-individual differences in neural “efficiency” (e.g., how efficient an individual’s brain is at processing information) during a variety of cognitive computations (He, 2014). For example, in the context of artificial language learning, a shallower $1/f$ slope during grammar acquisition has been associated with a better ability to learn various grammatical rules, explaining behavioural gains over and above that of more traditional measures (Cross, Corcoran, et al., 2020). However, it is currently unknown whether aperiodic activity is related to how individuals process tasks and how they come together during team decision-making. Given that aperiodic neural activity can be estimated from both task-related and resting-state EEG recordings (see Figure 4 for an example of aperiodic activity isolated from task-related and resting-state EEG), it may serve as a powerful and simple-to-estimate marker of individual differences in complex team-related behaviour and managerial-related cognitive computations.

Figure 4. Example of oscillatory and aperiodic components of an eyes-closed resting-state two-minute EEG recording. (A) Spectral peak illustrating the individual alpha frequency, or the oscillatory component of the recording. (B) The aperiodic or $1/f$ distribution of the power spectrum. Note that the “dip” at roughly 10 Hz clearly corresponds to the oscillatory component in (A), reflecting this participant’s IAF. (C) Relationship between the $1/f$ slope (x-axis; left = steeper slope, right = shallower slope) and memory performance (d-prime; higher values indicate better memory performance).

Resting-state EEG recordings are simple and easy to obtain. As such, estimating the $1/f$ slope from resting-state recordings – which have been argued to be trait-like neural “fingerprints” (e.g., Demuru & Fraschini, 2020) – may glean insights into individual differences in, for example, attention during decision-making (for associations between the $1/f$ slope and working memory, see Voytek et al., 2015). That is, the $1/f$ slope could be used as a predictor in models examining managerial cognition that focus heavily on attention. As stated above, the slope reflects the balance between neural excitation and inhibition, with a steeper slope reflecting enhanced inhibition and a shallower slope indexing greater excitation (Donoghue et al., 2020). Further, as the slope is associated with different states of alertness or “cognitive readiness”, an individuals’ resting-state $1/f$ slope may be used as a trait-like marker of attentional capacity (somewhat analogous to the concept of attentional control in MOC research) during complex team decision-making (Alter, 2001; Feist, 1998; Furst, Ghisletta & Lubart, 2014). In this way, the $1/f$ slope could be used to index changes in state (e.g., task-related) and trait (e.g., estimated from resting-state recordings) neural activity and used to predict fluctuations in attentional state and information processing capacity in managerial- and team-related behaviours. For example, the $1/f$ slope may become progressively shallower for difficult memory tasks (e.g., having to memorize aspects of a workplace policy handbook) and may predict how accurate an individual is when asked to recall specific details of the policy, particularly if having to generalise the information to novel work-related scenarios.

The EEG measures of individual differences (IAF and $1/f$ slope) introduced here have high test-retest reliability, are easy to obtain with EEG recordings, and are relatively simple to compute and analyse in comparison to current approaches of team performance and neurodynamics (e.g. (Gorman et al., 2019; Lamb et al., 2014; Stevens et al., 2017)). Further, the measures we have introduced here have been studied across a wide range of participant populations and experimental tasks, offering robust and generalisable insights into the neurobiological underpinnings of cognition. This allows future findings in the interdisciplinary space of organisational cognition to be more directly interpreted in the context of state-of-the-art neuroscience frameworks and theories. For example, future work could explore whether shared mental representations manifest through the combination of individuals with heterogenous or homogenous IAF estimates, or whether state- versus trait-level $1/f$ brain activity explains behaviour among team members.

Conclusion

Scholars who have recently started to work at the intersection of neuroscience (especially EEG) and management cognition (e.g. Balthazard et al., 2012; Peterson et al., 2008; Stevens & Galloway, 2014; Waldman et al., 2015), acknowledge that the applicability of neurobiological markers to management practice may not be immediately apparent. Some have even warned that identification of neurobiological markers and individual difference predictors of cognition and decision-making performance is likely to prime leaders to start making such indices part of the selection and placement criteria at work. We do not support such reductionism of human performance and caution readers to consider ethical safeguards before taking scientific knowledge at the intersection of neuroscience and management into practical applications.

Nevertheless, we propose that there are benefits in conducting research using triangulation of data from neuroscience and psychometrics to provide ecologically sound approaches to the assessment of established managerial cognition constructs at the individual and team level. By combining data from multiple sources (i.e., neurophysiological markers of cognition with perceptual and behavioural measures of decision-making), future research can avoid retrospective bias and gain greater insight into both the processes and outcomes of information processing. Some of these insights are likely to come from inductive and descriptive analyses of how neuro-markers of cognition correlate and overlap with perceptual and observed measures of information processing. Alternately, interesting insights and novel discoveries may arise if neuro-markers provide incremental or even contradictory predictions of decision-making after controlling for typically studied management constructs. There are many avenues for future research that include conducting basic fundamental research to identify how operationalized EEG markers relate to higher-level perceptual and behavioural measures of constructs such as attention, cognitive flexibility and shared cognition. We hope this chapter assists the next generation of organisational neuroscience scholars to develop new hypotheses in both the organisational and cognitive neuroscience fields.

References

- Academy of Management Managerial Organisational Cognition (MOC) Division. (n.d.). *Domain Statement*. <https://moc.aom.org/about-us/new-item3>
- Alamia, A., & VanRullen, R. (2019). Alpha oscillations and traveling waves: Signatures of predictive coding? *PLoS Biology*, *17*(10), e3000487.
- Arnal, L. H., & Giraud, A.-L. (2012). Cortical oscillations and sensory predictions. *Trends in Cognitive Sciences*, *16*(7), 390–398.
- Ashkanasy, N. M., Becker, W. J., & Waldman, D. A. (2014). Neuroscience and organizational behavior: Avoiding both neuro-euphoria and neuro-phobia. *Journal of Organizational Behavior*, *35*(7), 909–919.
- Balleine, B. W. (2007). The neural basis of choice and decision making. *Journal of Neuroscience*, *27*(31), 8159–8160.
- Balthazard, P. A., Waldman, D. A., Thatcher, R. W., & Hannah, S. T. (2012). Differentiating transformational and non-transformational leaders on the basis of neurological imaging. *The Leadership Quarterly*, *23*(2), 244–258.
- Barraza, P., Pérez, A., & Rodríguez, E. (2020). Brain-to-Brain Coupling in the Gamma-Band as a Marker of Shared Intentionality. *Frontiers in Human Neuroscience*, *14*.
<https://doi.org/10.3389/fnhum.2020.00295>
- Bastos, André M., Lundqvist, M., Waite, A. S., Kopell, N., & Miller, E. K. (2020). Layer and rhythm specificity for predictive routing. *Proceedings of the National Academy of Sciences*, 202014868.
<https://doi.org/10.1073/pnas.2014868117>
- Bastos, Andre M., Usrey, W. M., Adams, R. A., Mangun, G. R., Fries, P., & Friston, K. J. (2012). Canonical Microcircuits for Predictive Coding. *Neuron*, *76*(4), 695–711.
<https://doi.org/10.1016/j.neuron.2012.10.038>
- Berger, H. (1929). Über das elektroenkephalogramm des menschen. *Archiv Für Psychiatrie Und Nervenkrankheiten*, *87*(1), 527–570.
- Berka, C., Levendowski, D. J., Cvetinovic, M. M., Petrovic, M. M., Davis, G., Lumicao, M. N., Zivkovic, V. T., Popovic, M. V., & Olmstead, R. (2004). Real-Time Analysis of EEG Indexes of Alertness, Cognition, and Memory Acquired With a Wireless EEG Headset. *International Journal of Human-Computer Interaction*, *17*(2), 151–170.
https://doi.org/10.1207/s15327590ijhc1702_3
- Berka, C., Levendowski, D. J., Lumicao, M. N., Yau, A., Davis, G., Zivkovic, V. T., Olmstead, R. E., Tremoulet, P. D., & Craven, P. L. (2007). EEG correlates of task engagement and mental workload in vigilance, learning, and memory tasks. *Aviation, Space, and Environmental Medicine*, *78*(5), B231–B244.
- Bevilacqua, D., Davidesco, I., Wan, L., Chaloner, K., Rowland, J., Ding, M., Poeppel, D., & Dikker, S. (2019). Brain-to-brain synchrony and learning outcomes vary by student–teacher dynamics: Evidence from a real-world classroom electroencephalography study. *Journal of Cognitive Neuroscience*, *31*(3), 401–411.
- Bornkessel-Schlesewsky, I., Philipp, M., Alday, P. M., Kretzschmar, F., Grewe, T., Gumpert, M., Schumacher, P. B., & Schlewsky, M. (2015). Age-related changes in predictive capacity versus internal model adaptability: Electrophysiological evidence that individual differences outweigh effects of age. *Frontiers in Aging Neuroscience*, *7*, 217.
- Bornkessel-Schlesewsky, I., & Schlewsky, M. (2019). Toward a Neurobiologically Plausible Model of Language-Related, Negative Event-Related Potentials. *Frontiers in Psychology*, *10*.
<https://doi.org/10.3389/fpsyg.2019.00298>

- Bornkessel-Schlesewsky, I., Staub, A., & Schlewsky, M. (2016). The timecourse of sentence processing in the brain. In *Neurobiology of language* (pp. 607–620). Elsevier.
- Butler, M. J., & Senior, C. (2007). Toward an organizational cognitive neuroscience. *Annals of the New York Academy of Sciences*, 1118(1), 1–17.
- Cooke, N. J., & Gorman, J. C. (2009). Interaction-based measures of cognitive systems. *Journal of Cognitive Engineering and Decision Making*, 3(1), 27–46.
- Cooke, N. J., Gorman, J. C., & Rowe, L. J. (2004). *An Ecological Perspective on Team Cognition*: Defense Technical Information Center. <https://doi.org/10.21236/ADA525964>
- Cooke, N. J., Salas, E., Cannon-Bowers, J. A., & Stout, R. J. (2000). Measuring team knowledge. *Human Factors*, 42(1), 151. Agricultural & Environmental Science Collection; Art, Design & Architecture Collection; Earth, Atmospheric & Aquatic Science Collection; ProQuest One Academic; Technology Collection.
- Corcoran, A. W., Alday, P. M., Schlewsky, M., & Bornkessel-Schlesewsky, I. (2018). Toward a reliable, automated method of individual alpha frequency (IAF) quantification. *Psychophysiology*, 55(7), e13064.
- Cropanzano, R., & Becker, W. J. (2013). The promise and peril of organizational neuroscience: Today and tomorrow. *Journal of Management Inquiry*, 22(3), 306–310.
- Cross, Z. R., Corcoran, A. W., Schlewsky, M., Kohler, M. J., & Bornkessel-Schlesewsky, I. (2020). Oscillatory and aperiodic neural activity jointly predict grammar learning. *BioRxiv*.
- Cross, Z. R., Santamaria, A., Corcoran, A. W., Chatburn, A., Alday, P. M., Coussens, S., & Kohler, M. J. (2020). Individual alpha frequency modulates sleep-related emotional memory consolidation. *Neuropsychologia*, 148, 107660.
- Daitch, A. L., Sharma, M., Roland, J. L., Astafiev, S. V., Bundy, D. T., Gaona, C. M., Snyder, A. Z., Shulman, G. L., Leuthardt, E. C., & Corbetta, M. (2013). Frequency-specific mechanism links human brain networks for spatial attention. *Proceedings of the National Academy of Sciences*, 110(48), 19585–19590.
- Dave, S., Brothers, T., & Swaab, T. (2018). 1/f neural noise and electrophysiological indices of contextual prediction in aging. *Brain Research*, 1691, 34–43.
- Davidesco, I., & Milne, C. (2019). Implementing Cognitive Science and Discipline-Based Education Research in the Undergraduate Science Classroom. *CBE—Life Sciences Education*, 18(3), es4.
- Debener, S., Ullsperger, M., Siegel, M., & Engel, A. K. (2006). Single-trial EEG–fMRI reveals the dynamics of cognitive function. *Trends in Cognitive Sciences*, 10(12), 558–563.
- DeChurch, L. A., & Mesmer-Magnus, J. R. (2010). Measuring shared team mental models: A meta-analysis. *Group Dynamics: Theory, Research, and Practice*, 14(1), 1–14. <https://doi.org/10.1037/a0017455>
- Dikker, S., Wan, L., Davidesco, I., Kaggen, L., Oostrik, M., McClintock, J., Rowland, J., Michalareas, G., Van Bavel, J. J., Ding, M., & Poeppel, D. (2017). Brain-to-Brain Synchrony Tracks Real-World Dynamic Group Interactions in the Classroom. *Current Biology*, 27(9), 1375–1380. <https://doi.org/10.1016/j.cub.2017.04.002>
- Dodel, S., Tognoli, E., & Kelso, J. A. S. (2020). Degeneracy and Complexity in Neuro-Behavioral Correlates of Team Coordination. *Frontiers in Human Neuroscience*, 14. <https://doi.org/10.3389/fnhum.2020.00328>
- Donoghue, T., Haller, M., Peterson, E. J., Varma, P., Sebastian, P., Gao, R., Noto, T., Lara, A. H., Wallis, J. D., Knight, R. T., Shestyuk, A., & Voytek, B. (2020). Parameterizing neural power spectra into periodic and aperiodic components. *Nature Neuroscience*, 23(12), 1655–1665. <https://doi.org/10.1038/s41593-020-00744-x>

- Fellner, M.-C., Gollwitzer, S., Rampp, S., Kreiselmeier, G., Bush, D., Diehl, B., Axmacher, N., Hamer, H., & Hanslmayr, S. (2019). Spectral fingerprints or spectral tilt? Evidence for distinct oscillatory signatures of memory formation. *PLoS Biology*, 17(7), e3000403.
- Feuerriegel, D., Churches, O., Coussens, S., & Keage, H. A. (2018). Evidence for spatiotemporally distinct effects of image repetition and perceptual expectations as measured by event-related potentials. *NeuroImage*, 169, 94–105.
- Friston, K. (2010). The free-energy principle: A unified brain theory? *Nature Reviews Neuroscience*, 11(2), 127–138. <https://doi.org/10.1038/nrn2787>
- Friston, K., Adams, R., Perrinet, L., & Breakspear, M. (2012). Perceptions as hypotheses: Saccades as experiments. *Frontiers in Psychology*, 3, 151.
- Galotti, K. M., Tandler, J. M., & Wiener, H. J. (2014). Real-life decision making in college students II: Do individual differences show reliable effects? *The American Journal of Psychology*, 127(1), 33–42.
- Gorman, J. C., Grimm, D. A., Stevens, R. H., Galloway, T., Willemsen-Dunlap, A. M., & Halpin, D. J. (2019). Measuring Real-Time Team Cognition During Team Training. *Human Factors*, 0018720819852791. <https://doi.org/10.1177/0018720819852791>
- He, B. J. (2014). Scale-free brain activity: Past, present, and future. *Trends in Cognitive Sciences*, 18(9), 480–487. <https://doi.org/10.1016/j.tics.2014.04.003>
- He, B. J., Zempel, J. M., Snyder, A. Z., & Raichle, M. E. (2010). The Temporal Structures and Functional Significance of Scale-free Brain Activity. *Neuron*, 66(3), 353–369. <https://doi.org/10.1016/j.neuron.2010.04.020>
- Healey, M. P., & Hodgkinson, G. P. (2014). Rethinking the philosophical and theoretical foundations of organizational neuroscience: A critical realist alternative. *Human Relations*, 67(7), 765–792.
- Hedgcock, W., & Rao, A. R. (2009). Trade-off aversion as an explanation for the attraction effect: A functional magnetic resonance imaging study. *Journal of Marketing Research*, 46(1), 1–13.
- Heekeren, H. R., Marrett, S., & Ungerleider, L. G. (2008). The neural systems that mediate human perceptual decision making. *Nature Reviews Neuroscience*, 9(6), 467–479.
- Helfat, C. E., & Peteraf, M. A. (2015). Managerial cognitive capabilities and the microfoundations of dynamic capabilities. *Strategic Management Journal*, 36(6), 831–850. <https://doi.org/10.1002/smj.2247>
- Helfrich, R. F., & Knight, R. T. (2016). Oscillatory dynamics of prefrontal cognitive control. *Trends in Cognitive Sciences*, 20(12), 916–930.
- Hodgkinson, G. P., & Healey, M. P. (2008). Cognition in organizations. *Annual Review of Psychology*, 59.
- Huang, Y., & Rao, R. P. N. (2011). Predictive coding. *WIREs Cognitive Science*, 2(5), 580–593. <https://doi.org/10.1002/wcs.142>
- İnce, R., Adanır, S. S., & Sevmey, F. (2020). The inventor of electroencephalography (EEG): Hans Berger (1873–1941). *Child's Nervous System*. <https://doi.org/10.1007/s00381-020-04564-z>
- Klimesch, W. (1999). EEG alpha and theta oscillations reflect cognitive and memory performance: A review and analysis. *Brain Research Reviews*, 29(2), 169–195. [https://doi.org/10.1016/S0165-0173\(98\)00056-3](https://doi.org/10.1016/S0165-0173(98)00056-3)
- Klimesch, W. (2012). Alpha-band oscillations, attention, and controlled access to stored information. *Trends in Cognitive Sciences*, 16(12), 606–617. <https://doi.org/10.1016/j.tics.2012.10.007>
- Klimesch, W., Sauseng, P., & Hanslmayr, S. (2007). EEG alpha oscillations: The inhibition–timing hypothesis. *Brain Research Reviews*, 53(1), 63–88. <https://doi.org/10.1016/j.brainresrev.2006.06.003>

- Klimoski, R., & Mohammed, S. (1994). Team Mental Model: Construct or Metaphor? *Journal of Management*, 20(2), 403–437. <https://doi.org/10.1177/014920639402000206>
- Knight, R. T., Grabowecy, M. F., & Scabini, D. (1995). *Role of human prefrontal cortex in attention control*.
- Knight, R. T., Staines, W. R., Swick, D., & Chao, L. L. (1999). Prefrontal cortex regulates inhibition and excitation in distributed neural networks. *Acta Psychologica*, 101(2–3), 159–178.
- Kolm, J., Stevens, R., & Galloway, T. (2013). How Long Is the Coastline of Teamwork? In D. D. Schmorrow & C. M. Fidopiastis (Eds.), *Foundations of Augmented Cognition* (pp. 162–171). Springer Berlin Heidelberg.
- Kyriaki, L., Schlesewsky, M., & Bornkessel-Schlesewsky, I. (2020). Semantic reversal anomalies under the microscope: Task and modality influences on language-associated event-related potentials. *European Journal of Neuroscience*. <https://doi.org/10.1111/ejn.14862>
- Lamb, C., Lamb, J., Stevens, R., & Caras, A. (2014). Team Behaviors and Cognitive Cohesion in Complex Situations. In D. D. Schmorrow & C. M. Fidopiastis (Eds.), *Foundations of Augmented Cognition. Advancing Human Performance and Decision-Making through Adaptive Systems* (pp. 136–147). Springer International Publishing.
- Langan-Fox, J., Code, S., & Langfield-Smith, K. (2000). Team Mental Models: Techniques, Methods, and Analytic Approaches. *Human Factors: The Journal of the Human Factors and Ergonomics Society*, 42(2), 242–271. <https://doi.org/10.1518/001872000779656534>
- Laureiro Martinez, D., Brusoni, S., & Zollo, M. (2009). *COGNITIVE FLEXIBILITY IN DECISION MAKING: A NEUROLOGICAL MODEL OF LEARNING AND CHANGE*.
- Laureiro-Martinez, D. (2017). Chapter 11: How Do Managers Really Think? Using Think Aloud and fMRI to Take a Closer Look at Managerial Cognition. In R. J. Galavan, K. J. Sund, & G. P. Hodgkinson (Eds.), *New Horizons in Managerial and Organizational Cognition* (Vol. 2, pp. 279–314). Emerald Publishing Limited. <https://doi.org/10.1108/S2397-52102017011>
- Laureiro-Martínez, D., & Brusoni, S. (2018). Cognitive flexibility and adaptive decision-making: Evidence from a laboratory study of expert decision makers. *Strategic Management Journal*, 39(4), 1031–1058. <https://doi.org/10.1002/smj.2774>
- Laureiro-Martínez, D., Brusoni, S., Canessa, N., & Zollo, M. (2015). Understanding the exploration–exploitation dilemma: An fMRI study of attention control and decision-making performance. *Strategic Management Journal*, 36(3), 319–338.
- Lendner, J. D., Helfrich, R. F., Mander, B. A., Romundstad, L., Lin, J. J., Walker, M. P., Larsson, P. G., & Knight, R. T. (2020). An electrophysiological marker of arousal level in humans. *ELife*, 9, e55092. <https://doi.org/10.7554/eLife.55092>
- Levine, R., & Zervos, S. J. (1993). What we have learned about policy and growth from cross-country regressions? *The American Economic Review*, 83(2), 426–430.
- Lewis, A. G., & Bastiaansen, M. (2015). A predictive coding framework for rapid neural dynamics during sentence-level language comprehension. *Cortex*, 68, 155–168.
- Lindebaum, D. (2013). Pathologizing the healthy but ineffective: Some ethical reflections on using neuroscience in leadership research. *Journal of Management Inquiry*, 22(3), 295–305.
- Lindquist, K. A., Wager, T. D., Kober, H., Bliss-Moreau, E., & Barrett, L. F. (2012). The brain basis of emotion: A meta-analytic review. *The Behavioral and Brain Sciences*, 35(3), 121.
- Lipshitz, R., & Bar-Ilan, O. (1996). How problems are solved: Reconsidering the phase theorem. *Organizational Behavior and Human Decision Processes*, 65(1), 48–60. <https://doi.org/10.1006/obhd.1996.0004>
- Luck, S. J. (2014). *An introduction to the event-related potential technique*. MIT press.

- Luck, S. J., Woodman, G. F., & Vogel, E. K. (2000). Event-related potential studies of attention. *Trends in Cognitive Sciences*, 4(11), 432–440.
- Marois, R., & Ivanoff, J. (2005). Capacity limits of information processing in the brain. *Trends in Cognitive Sciences*, 9(6), 296–305.
- Massaro, S. (2017). Chapter 10: Neuroscience Methods: A Framework for Managerial and Organizational Cognition. In R. J. Galavan, K. J. Sund, & G. P. Hodgkinson (Eds.), *New Horizons in Managerial and Organizational Cognition* (Vol. 2, pp. 241–278). Emerald Publishing Limited. <https://doi.org/10.1108/S2397-52102017010>
- McLagan, P. A. (2013). A call to watch our paradigms! *Journal of Management Inquiry*, 22(3), 314–316.
- Miller, E. K. (2000). The prefrontal cortex and cognitive control. *Nature Reviews Neuroscience*, 1(1), 59–65.
- Min, B.-K., & Park, H.-J. (2010). Task-related modulation of anterior theta and posterior alpha EEG reflects top-down preparation. *BMC Neuroscience*, 11(1), 1–8.
- Mohammed, S., Ferzandi, L., & Hamilton, K. (2010). Metaphor No More: A 15-Year Review of the Team Mental Model Construct. *Journal of Management*, 36(4), 876–910. <https://doi.org/10.1177/0149206309356804>
- Niv, Y. (2020). *The primacy of behavioral research for understanding the brain*.
- Ocasio, W. (2011). Attention to Attention. *Organization Science*, 22(5), 1286–1296. <https://doi.org/10.1287/orsc.1100.0602>
- Ouyang, G., Hildebrandt, A., Schmitz, F., & Herrmann, C. S. (2020). Decomposing alpha and 1/f brain activities reveals their differential associations with cognitive processing speed. *NeuroImage*, 205, 116304.
- Peterson, S. J., Balthazard, P. A., Waldman, D. A., & Thatcher, R. W. (2008). Neuroscientific Implications of Psychological Capital: Are the Brains of Optimistic, Hopeful, Confident, and Resilient Leaders Different? *Organizational Dynamics*, 37(4), 342–353.
- Porac, J. (2015). Managerial and Organizational Cognition. In C. L. Cooper (Ed.), *Wiley Encyclopedia of Management* (pp. 1–2). John Wiley & Sons, Ltd. <https://doi.org/10.1002/9781118785317.weom110186>
- Posner, M. I., & DiGirolamo, G. J. (2000). Cognitive neuroscience: Origins and promise. *Psychological Bulletin*, 126(6), 873.
- Prinzel, L. J., Freeman, F. G., Scerbo, M. W., Mikulka, P. J., & Pope, A. T. (2000). A closed-loop system for examining psychophysiological measures for adaptive task allocation. *The International Journal of Aviation Psychology*, 10(4), 393–410.
- Prinzel, L. J., Freeman, F. G., Scerbo, M. W., Mikulka, P. J., & Pope, A. T. (2003). Effects of a psychophysiological system for adaptive automation on performance, workload, and the event-related potential P300 component. *Human Factors*, 45(4), 601–614.
- Reinero, D. A., Dikker, S., & Van Bavel, J. J. (2020). Inter-brain synchrony in teams predicts collective performance. *Social Cognitive and Affective Neuroscience*.
- Rouhani, N., Norman, K. A., & Niv, Y. (2018). Dissociable effects of surprising rewards on learning and memory. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, 44(9), 1430.
- Rouhani, N., Norman, K. A., Niv, Y., & Bornstein, A. M. (2020). Reward prediction errors create event boundaries in memory. *Cognition*, 203, 104269. <https://doi.org/10.1016/j.cognition.2020.104269>
- Sadaghiani, S., & Kleinschmidt, A. (2016). Brain networks and α -oscillations: Structural and functional foundations of cognitive control. *Trends in Cognitive Sciences*, 20(11), 805–817.

- Samaha, J., & Postle, B. R. (2015). The Speed of Alpha-Band Oscillations Predicts the Temporal Resolution of Visual Perception. *Current Biology*, 25(22), 2985–2990. <https://doi.org/10.1016/j.cub.2015.10.007>
- Senior, C., Lee, N., & Butler, M. (2011). PERSPECTIVE—Organizational Cognitive Neuroscience. *Organization Science*, 22(3), 804–815. <https://doi.org/10.1287/orsc.1100.0532>
- Sheehan, T. C., Sreekumar, V., Inati, S. K., & Zaghloul, K. A. (2018). Signal complexity of human intracranial EEG tracks successful associative-memory formation across individuals. *Journal of Neuroscience*, 38(7), 1744–1755.
- Simon, H. A. (1955). A Behavioral Model of Rational Choice. *The Quarterly Journal of Economics*, 69(1), 99. <https://doi.org/10.2307/1884852>
- Spratling, M. W. (2008). Predictive coding as a model of biased competition in visual attention. *Vision Research*, 48(12), 1391–1408.
- Stevens, R., Galloway, T., Campbell, G., Berka, C., & Balthazard, P. (2013). How Tasks Help Shape the Neurodynamic Rhythms and Organizations of Teams. In D. D. Schmorow & C. M. Fidopiastis (Eds.), *Foundations of Augmented Cognition* (pp. 199–208). Springer Berlin Heidelberg.
- Stevens, R., Galloway, T., & Lamb, C. (2014). Submarine Navigation Team Resilience: Linking EEG and Behavioral Models. *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, 58(1), 245–249. <https://doi.org/10.1177/1541931214581051>
- Stevens, R., Galloway, T., Lamb, J., Steed, R., & Lamb, C. (2017). Linking Team Neurodynamic Organizations with Observational Ratings of Team Performance. In A. A. von Davier, M. Zhu, & P. C. Kyllonen (Eds.), *Innovative Assessment of Collaboration* (pp. 315–330). Springer International Publishing. https://doi.org/10.1007/978-3-319-33261-1_20
- Stevens, R., Galloway, T., Wang, P., Berka, C., Tan, V., Wohlgemuth, T., Lamb, J., & Buckles, R. (2013). Modeling the neurodynamic complexity of submarine navigation teams. *Computational and Mathematical Organization Theory*, 19(3), 346–369. <https://doi.org/10.1007/s10588-012-9135-9>
- Stevens, R. H., Galloway, T., Berka, C., & Sprang, M. (2009). Can neurophysiologic synchronies be detected during collaborative teamwork. *Proceedings: HCI International*, 19–24.
- Stevens, R. H., & Galloway, T. L. (2014). Toward a quantitative description of the neurodynamic organizations of teams. *Social Neuroscience*, 9(2), 160–173. <https://doi.org/10.1080/17470919.2014.883324>
- Stevens, R. H., & Galloway, T. L. (2017). Are Neurodynamic Organizations A Fundamental Property of Teamwork? *Frontiers in Psychology*, 8. <https://doi.org/10.3389/fpsyg.2017.00644>
- Stevens, R. H., & Galloway, T. L. (2019). Teaching Machines to Recognize Neurodynamic Correlates of Team and Team Member Uncertainty. *Journal of Cognitive Engineering and Decision Making*, 155534341987456. <https://doi.org/10.1177/1555343419874569>
- Summerfield, C., & Egner, T. (2009). Expectation (and attention) in visual cognition. *Trends in Cognitive Sciences*, 13(9), 403–409.
- Sweeney-Reed, C. M., Zaehle, T., Voges, J., Schmitt, F. C., Buentjen, L., Kopitzki, K., Hinrichs, H., Heinze, H.-J., Rugg, M. D., & Knight, R. T. (2015). Thalamic theta phase alignment predicts human memory formation and anterior thalamic cross-frequency coupling. *Elife*, 4, e07578.
- Voloh, B., Valiante, T. A., Everling, S., & Womelsdorf, T. (2015). Theta–gamma coordination between anterior cingulate and prefrontal cortex indexes correct attention shifts. *Proceedings of the National Academy of Sciences*, 112(27), 8457–8462.

- von Nicolai, C., Engler, G., Sharott, A., Engel, A. K., Moll, C. K., & Siegel, M. (2014). Corticostriatal coordination through coherent phase-amplitude coupling. *Journal of Neuroscience*, 34(17), 5938–5948.
- Voytek, B., Kramer, M. A., Case, J., Lepage, K. Q., Tempesta, Z. R., Knight, R. T., & Gazzaley, A. (2015). Age-related changes in 1/f neural electrophysiological noise. *Journal of Neuroscience*, 35(38), 13257–13265.
- Waldman, D. A., Wang, D., Stikic, M., Berka, C., & Korszen, S. (2015). Neuroscience and Team Processes. In D. A. Waldman & P. A. Balthazard (Eds.), *Monographs in Leadership and Management* (Vol. 7, pp. 277–294). Emerald Group Publishing Limited.
<https://doi.org/10.1108/S1479-357120150000007012>
- Waldman, D. A., Ward, M. K., & Becker, W. J. (2017). Neuroscience in Organizational Behavior. *Annual Review of Organizational Psychology and Organizational Behavior*, 4(1), 425–444.
<https://doi.org/10.1146/annurev-orgpsych-032516-113316>
- Walsh, J. P. (1995). Managerial and Organizational Cognition: Notes from a Trip Down Memory Lane. *Organization Science*, 6(3), 280–321. JSTOR.
- Wildman, J. L., Salas, E., & Scott, C. P. R. (2014). Measuring Cognition in Teams: A Cross-Domain Review. *Human Factors: The Journal of the Human Factors and Ergonomics Society*, 56(5), 911–941. <https://doi.org/10.1177/0018720813515907>
- Woodman, G. F. (2010). A brief introduction to the use of event-related potentials in studies of perception and attention. *Attention, Perception, & Psychophysics*, 72(8), 2031–2046.
- Yeung, M. K., Han, Y. M., Sze, S. L., & Chan, A. S. (2016). Abnormal frontal theta oscillations underlie the cognitive flexibility deficits in children with high-functioning autism spectrum disorders. *Neuropsychology*, 30(3), 281.