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**A ROLE FOR ENDOGENOUS BRAIN STATES IN ORGANIZATIONAL RESEARCH:  
MOVING TOWARDS A DYNAMIC VIEW OF COGNITIVE PROCESSES**

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*Life is a series of collisions with the future; it is not the sum of what we have been, but what we yearn to be. Jose Ortega y Gasset*

A leader summons her team for a meeting – substantial changes within the organization are on the agenda, and what Ortega y Gasset colorfully terms ‘collisions with the future’ are beginning to unfold. Despite all preparations, up to and including taking into account insights from state-of-the-art organizational research, the leader is likely to face a complex mélange of non-negotiable facts, fluid social networks, and internal environments, creating unpredictability and tension that the leader is required to negotiate to be successful (Hannah, Schaubroeck & Peng, 2015). The team members will collide too. Long held plans may or may not bear out, or avenues for improvement previously considered closed may become newly-open during negotiations. Who can predict the precise outcome? Will the team members accept the propositions or consider them unacceptable and fight back as strong as legally possible?

Many aspects of this perhaps not-so-hypothetical scenario above are amenable to investigation using traditional neuroscience methodology, employing well-controlled experimental protocols and stimuli, where individual factors such as mood state or vigilance may be used as regression variables for analysis. Such stimulus- or event-based approaches are dominant in neuroscience, including functional neuroimaging, where the brain is seen as an essentially reactive system. Accordingly, some sensory input causes some neural activity, which in turn results in some important response such as for example a motor activity, or some hypothesized higher-level cognitive or affective process (Bechtel & Abrahamsen, 2010a; Raichle & Snyder, 2007). This approach has its roots in Sherrington’s (1906) early work, and has underpinned most existing neuroscience work, leading to enormous advances in our understanding of the brain’s structure, operation, and functional organization. In this view, the

brain is primarily driven by the demands of the environment, and brain activity that is not in response to some input is regarded as noise. It is not overstating the case to suggest that this reactive approach is the foundation for cognitive science in general.

The reactive view, however, has limitations. It has been demonstrated over and over that the behavioral response can be highly variable given a constant set of stimulus parameters, and controlling for factors such as trial history and fatigue. For example even basic response times to salient stimulation can exhibit a 4- to 5-fold intra-subject variability. Commonly, variability is considered ‘noise’, explained to some extent by theories of stochastic neuronal networks, and taken out of consideration through averaging or other statistical manipulation of data. This is approach is unfortunate for two reasons. First, there is reason to assume that response variability is important to free a being from stereotypic and predictable behavioral patterns in order to adaptively respond to changes in the environment. This, for example, is reflected in certain models of sensori-motor processes explicitly linking variability in reaction time to variability in choice or decision outcome (see, e.g., Bompas, Sumner, Muthumumaraswamy, Singh & Gilchrist, 2015). Second, it ignores the possibility that the apparent fluctuations in behavior are related to, and to some extent are predicted by, the endogenous brain activity present at all times. The latter possibility could be termed the intrinsic view, and is essentially based on Hebbian reasoning, expressed magisterially many decades ago: “ ... *It is therefore impossible that the consequence of a sensory event should often be uninfluenced by the existing activity ...* ” (Hebb, 1949 cited in Sporns, 2011 p. 149). Regrettably though, it appears the quick progress of knowledge from experimental event-related methods, which imply a reactive view, has led to a general ignorance of the intrinsic (endogenous) view.

Unsurprisingly, given the dominance of the reactive view of brain function in neuroscience and psychology in general, the recent growth of neuroscience-based research in the organizational sciences has been entirely based on the reactive view. In this paper, we wish to make a case for an increased consideration of the intrinsic view of brain activity, and explain the basic conceptual and methodological principles behind the study of endogenous brain activity (EBA) and its influence on responses relevant to organizational research. Importantly, we will show that EBA is not merely of interest to basic neuroscience, but has major implications for the theory and practice of organizational research in many different ways. Indeed, we hope to convince readers that without considering EBA, organizational researchers can never provide more than a partial picture of human behavior in organizational contexts.

Further, we will show how consideration of EBA helps to respond to recent challenges to organizational cognitive neuroscience regarding theories and methodologies (see Senior, Lee, & Butler, 2011), as well as to recent skepticism about the feasibility and usefulness of neuroscience based approaches to organizational research (see Lindebaum, 2016). We will argue that incorporating an understanding of the role of EBA in social and organizational behavior helps to move beyond the restrictions of a reactive approach and associated subtractive methodology (i.e. the binary mapping of firing / dormant neurons in a specific brain region in response to some isolated stimulus). Taking account of EBA considers the brain in its entirety, as a continuously operating cognitive unit that processes the complexity of our social interactions and responds appropriately, thereby revolutionizing our understanding of the brain in organizational research.

## **AN INTRODUCTION TO ENDOGENOUS BRAIN ACTIVITY**

The brain is never inactive. Obviously, one might think. As with all organs in the human body the brain's cells are constantly engaged in the highly complex biochemical processing necessary to maintain the homeostasis needed to stay alive. However, there is more to the high levels of intrinsically generated neuronal activity occurring continuously than basic homeostasis. Such spontaneous activity, also called resting or ongoing activity, is not limited to subcortical, life-maintaining structures and can be detected throughout the brain's cortical regions, reflecting neuronal communication not attributable to specific inputs or outputs (Fox & Raichle, 2007). Already known to exist in the late 19<sup>th</sup> century, the nature of the brain's spontaneous activity has only recently been clarified through advances in neuroscience. It is now generally accepted that the brain's resting activity is not simply neuronal noise but rather exhibits specific patterns of coherence of neuronal processes reflecting to some degree the underlying global and local neuroanatomy (Fox, Snyder, Vincent, Corbetta, Van Essen & Raichle, 2005; Damoiseaux, Rombouts, Barkhof, Scheltens, Stam, Smith et al, 2006 and see Biswal, 2012).

Such patterns are observable across different behavioral states, including different resting conditions, sleep, and even anesthesia (Scholvincka, Maiera, Yec, Duynd & Leopold, 2010). The mechanisms underlying spontaneous firing are complex, where, at one end of the spectrum, genetic factors (Wang, Belgard, Mao, Chen, Berto, Preuss et. al., 2015) are likely to play a role and, at the other end, environmental factors and learning can impact the patterns of activity (Lewis, Baldassarre, Committeri, Romani & Corbetta, 2009). It is generally agreed, however, that the coherence patterns observed in spontaneous activity are not simply due to unconstrained tasks or conscious mentation. In other words, the brain's resting activity goes beyond processes related to mental tasks, spontaneously occurring in situations without explicit task demands (Fox & Raichle, 2007).

For example, a well-documented coherence pattern is the default mode network that has been implicated in, amongst others, social cognition and emotional self-awareness (Schilbach, Eickhoff, Rotarska-Jagiela, Fink, & Vogeley, 2008; aspects of the default mode network relevant to organizational research are discussed in Boyatzis, Rochford & Jack, 2014). Evidence obtained mainly from metabolism based (i.e., fMRI) studies suggests that brain areas that are similarly modulated by various task paradigms tend also to be correlated in their spontaneous activity measured at rest (Fox & Raichle, 2007). Over and above rest versus task comparisons, so-called pre-stimulus designs are of utmost importance here. Such studies directly investigate the relationship between the omnipresent spontaneous activity and event-related activity elicited by tightly controlled stimuli.

Two general and interrelated observations are relevant at this point. First, the event-related increase in neuronal metabolism is generally minute compared to the vast amount of energy needed to maintain resting activity (about 20% of the body's basal metabolic rate), even under demanding task conditions (Raichle & Mintun, 2006). This implies that stimulus and/or task driven neuronal processing is not simply matter of enhanced mental efforts draining more of the available energy but rather matter of temporarily redistributing energy across brain regions and reorganizing the dynamic makeup of neuronal networks without necessarily altering overall energy expenditure.

Second, there is consensus that spontaneous activity accounts to some extent for the inter-trial variability of event-related neuronal response observed within subjects under otherwise identical task conditions (Mennes, Kelly, Zuo, Di Martino, Biswal & Castellanos, 2010). This interaction between spontaneous and event-related is increasingly being recognized as a complex, non-linear process featuring distinct and reproducible patterns (Huang, Zhang, Longtin,

Dumont, Duncan, Pokorny et. al., 2015). Here, non-linearity is key, suggesting that event-related activity interacts dynamically with the spontaneous activity, rather than simply being added to it. From a system neuroscience perspective (e.g. Uddin & Menon, 2010), the precise nature of interaction between the two types of activities is yet unresolved. The evidence accumulated from mainly electrophysiological studies, however, points to a variety of possibly interrelated mechanisms. Amongst others, the spontaneous activity may reflect periodic variations in cortical excitability serving as a form of gain control for incoming neuronal responses (Chaumon & Busch, 2014). Alternatively, stimulation may enhance spontaneously formed and pre-existing (at the moment of stimulus arrival) causal interaction between brain regions (Lou, Joensuu, Biermann-Ruben, Schnitzler, Østergaard, Troels et.al., 2011).

Most important, the effect that pre-stimulus brain activity has on event-related neuronal processing extends to behavior, reinforcing the notion that the ongoing activity constitutes more than just inconsequential baseline variations (Kondakor, Lehmann, Michel, Brandeis, Kochi & Koenig, 1997). Before proceeding, it is worthwhile to look in more detail at some of the evidence obtained from a variety of pre-stimulus studies. Unless stated otherwise, the studies selected here have utilized EEG, quantifying pre-stimulus activity according to spectral power and/or (phase) coherence measures in the theta [4-7Hz], alpha [8-12Hz] and beta [13-30Hz] bands. Power and coherence measures may reflect different neurophysiological processes, where both types of measures provide information about brain dynamics beyond the understanding that can be extracted from the traditional evoked response, which is broadband in nature (i.e. includes all frequencies). In particular, synchrony of oscillations at higher frequency (> 20Hz) is thought to be fundamental property of neural systems, facilitating the coordinated interactions of large neuronal populations distributed within and across distinct regions of the brain; an interaction

deemed necessary for most cognitive processes (Tallon-Baudry, 2009). Thus, in the following, the different measures should not be regarded as interchangeable, but rather as neuronal manifestations that might converge on the same cognitive processes underlying endogenous brain states.

The most basic approaches to investigate pre-stimulus effects are near threshold study designs, where identical stimuli are weak, briefly presented, or adjusted otherwise such that target events are, on average, not detected, perceived or discriminated in a substantial proportion of trials (typically, 30 - 50%). Studies employing visual stimuli tend to concentrate on alpha activity, suggesting that strong pre-stimulus activity in that frequency band can reduce target detection rates for both optical stimuli (Chaumon & Busch, 2014) and phosphenes (illusory light flash) induced by transcranial magnetic stimulation (Romei, Brodbeck, Michel, Amedi, Pascual-Leone & Thut, 2008). There also evidence that the phase of the alpha wave present at stimulus onset can affect perceptual performance (Mathewson, Gratton, Fabiani, Beck & Ro, 2009), however, direct comparisons of phase effects across studies are difficult due to differences in methodologies. Also, there is evidence that pre-stimulus theta-phase can affect perceptual performance (Hanslmayr, Volberg, Wimber, Dalal & Greenlee, 2013).

An effect of both pre-stimulus alpha phase and power has also been reported for near threshold tactile perception. Notably, an inverted U-shaped relationship between pre-stimulus alpha power and detection rate has been reported, arguing against the assumption that performance is related monotonously to alpha power (Ai & Ro, 2014). Importantly, studies employing non-visual stimuli have also pointed to a role for beta oscillation. Judgments of simultaneity of tactile stimuli appear the more accurate the lower that pre-stimulus beta activity is (Lange, Halacz, van Dijk, Kahlbrock & Schnitzler, 2012), whereas order judgments of tones



played with a temporal offset appear to be more accurate the higher that pre-stimulus beta activity is (Bernasconi, Manuel, Murray & Spierer, 2011). Also, high pre-stimulus beta power can lead to higher accuracy of perceptual integration in missing element tasks (Geerligs & Akyürek, 2012).

The effects of pre-stimulus activity on behavior also extend to above-threshold situations. It has been suggested that pre-stimulus alpha power can make a distractor stimulus more potent (distracting attention away from the target), whereas faster response times (but no changes in accuracy) have been associated with high pre-stimulus alpha in visuomotor go/no-go (Vecchio, Lacidogna, Miraglia, Bramanti, Ferreri & Rossini, 2014) and simple target detection (Minkwitz, Trenner, Sander, Olbrich, Sheldrick, Schönknecht et. al., 2011) studies. Over and above basic perception and discrimination, studies probing various aspects of memory have provided valuable evidence that pre-stimulus activity can affect behavior thought to reflect higher order neuronal processes in specific ways, explored below.

Regarding memory (stimulus) encoding, it has been shown that pre-stimulus alpha power correlates negatively with memory accuracy for the upcoming stimulus in a task requiring the subjects to memorize a sequence of location-orientation associations (of simple shapes) to be recalled a few seconds later (Myers, Stokes, Walther & Nobre, 2014). Intracranial recordings from the hippocampus (a structure instrumental in memory formation) suggest that increased pre-encoding theta correlates with old-new recognition memory but not free recall of word stimuli (Merkow, Burke, Stein & Kahana, 2014). Interestingly, the latter authors employed a combined free recall (i.e. ‘name the words just memorized’) and recognition (i.e. ‘distinguish between new words’) task, where the latter happened several minutes after encoding. Pre-stimulus theta appears also to play a role in memory retrieval. A study utilizing word stimuli

reported enhanced theta-band power before presentation of test words eliciting both accurate old-new recognition and retrieval of contextual details of the prior study phase, compared to trials for which only recognition was successful (Addante, Watrous, Yonelinas, Ekstrom & Ranganath, 2011).

Further evidence that pre-stimulus activity influences higher order processes and behavior is provided by studies probing multi-sensory integration, in particular designs relying on the McGurk effect. This well-established effect shows the influence of visual stimuli on auditory perception, where mismatching information from both modalities can fuse to a novel percept that does not follow from either the auditory or the visual stimulus alone. Using MEG, it has been suggested that high pre-stimulus beta activity correlates with the rate of fused percepts (Keil, Müller, Ihssen & Weisz, 2012). Employing a variant of the McGurk effect, the so-called sound-induced flash illusion, the same team demonstrated that alpha and beta band activity as detected by MEG correlates with the rate of perceiving an illusory but non-existent flash (Keil, Müller, Hartmann & Weisz, 2014). Interestingly, pre-stimulus alpha-phase has also been linked to perceiving a similar illusion, where touch induces a flash instead of sound (van Erp, Philippi, de Winkel & Werkhoven, 2014).

Towards what are generally accepted as even higher processes, it has been demonstrated that pre-stimulus activity biases perceptual decisions on an ambiguous figure, such as Rubin's face-vase image. Evidence from fMRI suggests that activity in the fusiform face area, a brain region preferentially responding to faces, correlates with a subsequent face rather than vase percept (Hesselmann, Kell, Eger & Kleinschmidt, 2008). Using MEG to investigate the neuronal response to the same ambiguous figure, there is tentative evidence that pre-stimulus power in the alpha and beta bands correlates with subsequent face percepts (Peateld, Mueller, Ruhnau &

Weisz, 2015).

In summary, there is now converging evidence that the spontaneous activity affects, in complex ways, perception, cognitive control, and motor performance over and above the reactive response to stimuli. Electrophysiological approaches have been used most often as they are most sensitive to rapid neuronal dynamics, however, other imaging technologies have made significant contributions to the debate. Given that different technologies are differentially sensitive to neuronal mechanisms, this implies that pre-stimulus effects neither are quantifiable in terms of a single measure of neuronal activity nor are explainable in terms of a universal process, although modulation of attention might often play a role, particularly in the case of simple detection tasks. Also, there is still clarification required as to what extent pre-stimulus activity can explain the variance in the behavioral response to identical stimuli, as there are no definitive figures available at present.

Despite these limitations, it is reasonable to argue that the spontaneous activity reflects time-varying functional states of the brain, which affect the fate of an incoming stimulus within physiological constraints. These momentary brain states are assumed to reflect, in a dynamic fashion, internal models of the environment to anticipate and interpret sensory inputs and to prepare for action, much in the sense of Hebb's original reasoning (see also the discussion by Qian & Di, 2011). In this view, one moves away from the many constituting cellular sub-processes, towards the notion of a global brain state present at each moment in time, which, as abstract as it may sound, it is perhaps not less plausible than attaching a single figure, i.e., body temperature, to a bacterial infection despite extraordinarily complex immunological processes working to restore normality. That said, while insightful in a general neuroscientific sense, the electrophysiological studies reported above have utilized techniques essentially based on the

Fourier transform, named after the 18<sup>th</sup> century French mathematician Jean-Baptiste Fourier, in order to achieve signal representation in time and frequency. Although time-frequency decompositions can be justified by neuronal models to some extent, the techniques are very general in nature and do not easily relate to the notion of (brain) state. As such, we believe that a framework loosely termed *state-space reconstruction* would be most beneficial to organizational neuroscience at this stage. Given the importance and ramifications of the underlying theory, it is necessary to elaborate a little on its background, which we do below, before discussing a specific algorithm that can be used to represent the dynamic endogenous brain state.

### **NONLINEAR APPROACHES TO ENDOGENOUS BRAIN ACTIVITY**

Many interesting systems and phenomena in nature are complex, in particular – only few would doubt – the human brain. Complexity science is a relatively young area of research, which was treated with some skepticism (Horgan, 1995) in its early phases but is now very much *en vogue*, with 50 or more high profile research institutes around the world focusing on complex systems. Indeed, none other than Stephen Hawking expressed the view that the 21st century “will be the century of complexity” (Hawking, San Jose Mercury News, 23 January 2000).

Perhaps the most important contribution to the study of complex systems comes from the theory of nonlinear deterministic dynamical systems. The theory, which is deeply rooted in mathematics and theoretical physics, posits that certain systems can exhibit apparent randomness, making precise predictions of future states impossible for all practical purposes, despite the underlying dynamical laws being deterministic and thus allowing in principle exact predictions at all times (Tél & Gruiz, 2006). A hallmark of this apparent randomness (or chaotic

behavior) is sensitivity to initial conditions, implying that infinitesimally small uncertainties in knowledge of the current state of the system become exponentially large as time progresses. A concept often cited in this context is the ‘Butterfly Effect’ where small causes can have large effects (e.g. Hilborn, 2004).

*Chaos: When the present determines the future, but the approximate present does not approximately determine the future. Edward Lorenz*

One should not, however, simply equate complexity with nonlinear dynamics. There are complex systems without any apparent dynamical features (e.g., complex mechanical structures), dynamical complex systems that would not normally be explained in terms of nonlinear dynamics (e.g., game-theoretic dynamics), and linear complex systems (e.g., networks with linear response functions). This last point alludes also to the observation that although a system is nonlinear as a whole, some of its behavior (or at least to a good approximation), can be reduced to the sum of the behavior of the constituent parts (see, e.g., Bertuglia & Vaio, 2005). Ultimately, this is the justification of some approaches to the analysis of brain data, such as time-frequency analysis where a complex signal is assumed to be a linear superposition of waves localized at certain points in time and in distinct frequency bands.

There is now considerable evidence that nonlinear system theory applies to a variety of domains, including amongst others meteorology, stock markets, car traffic, biology (e.g., population growth models) and psychology (e.g., group dynamics). Most importantly for our purposes, the theory provides frameworks to recover certain features of a dynamical system from observations without knowledge of the underlying laws of the system, and only assuming that these laws have very general properties. State-space reconstruction is one such framework,

which is based on the assumption that an experimentally observed time series (e.g., an EEG or MEG trace) has been generated by a deterministic dynamical system, i.e., a system, which is described by the time evolution of a (typically small) fixed number of variables forming a trajectory in some suitable space, known as the state (or phase) space of the system (e.g., Stam, 2005). Critically, due to the deterministic nature of the system, the points in state space form, under certain conditions, sets (loosely speaking, attractors) with well-defined mathematical properties.

Dependent on the dynamics, such attractors can be simple shapes like points, lines, circles or surfaces, but often have a complex structure reflecting the system's sensitive dependence on initial conditions, which in turn relates to the apparent randomness a deterministic system can display (Tél & Gruiz, 2006). Thus, the complex but bounded structure of the attractor implies both local unpredictability and global stability; once trajectories have entered the attracting set, nearby points may rapidly diverge from one another but never depart from the attractor, reflecting the fact that the system's dynamics is bound by limitations imposed by physics, biology and physiology (e.g., a neuron's firing rate cannot be infinitely large because of cell membrane refractory periods). Typically, for real systems, the state space is not directly accessible and needs to be inferred from the observed data that are seen as an image of the trajectory under some, at best only partially-known, function constituting the measurement process. These concepts are illustrated in Fig. 1, and the below discussion.

<Figure 1 about here>

As a simple example (Fig. 1, upper row), one may imagine a pendulum swinging gently by an angle ( $\theta$ ) of a few degrees to the left and right ( $\theta$  is the position variable). Now, as the pendulum swings, one plots points in a coordinate system where the x-axis represents momentary angle ( $-\theta$  at leftmost deflection, 0 at center,  $\theta$  at right) and the y-axis represents momentary velocity (0 at turning points  $\pm\theta$ ,  $\pm v_{\max}$  [maximal velocity] at the center swinging to the right and left, respectively). Then, it turns out that one obtains a circle (Fig.1, upper row, right panel, solid line), which fully describes the dynamics of the swinging pendulum in a space spanned by angle of deflection and velocity of swing. More abstractly, the pendulum is in a circular state (which becomes larger and more deformed if one increases the angle of swing; turning into open, wavy lines for angles so large that the pendulum rotates around its suspension point [not shown]). In this scenario, plotting only the momentary angle as function of time (which turns out to be a sine wave) yields an observation (Fig. 1, upper row, middle panel).

The goal is then to re-build the original trajectory by a set of points extracted from the time series. These points are commonly defined as elements of a Euclidean space of some fixed dimension. Mathematical theories are needed to specify under which condition the reconstruction is faithful, i.e., the reconstructed trajectory reflects the geometrical and dynamical characteristic of the underlying dynamical system. This is critical as one has a framework based on first principles allowing one to study at least some aspects of the system without further knowledge of the underlying laws governing its dynamics. In principle, there are many measures one could apply to probe state space depending on what aspects of the dynamics are of interest (Faust & Bairy, 2012). Here, we focus on a particular method directly linked to the concept of determinism. The details of the procedure have been published in more depth elsewhere (Braeutigam & Swithenby, 2003; Braeutigam, 2007), and only a brief summary is provided here,

with interested readers referred to the cited works.

1) Suitable stretches of pre-stimulus data (i.e., multi-channel EEG or MEG recordings) are delay-embedded, yielding a trajectory in some  $n$ -dimensional space (e.g. for the pendulum, choose  $n=2$  and plot points  $(x_t, x_{t+\Delta})$ , where  $\Delta$  can be almost any value). The dimension  $n$  can be estimated in a data driven fashion using suitable algorithms. Note that there is one trajectory for each channel (with each channel referring to a local recording site, such as an electrode if using an EEG).

2) Compute a measure STL (STate Local) according to equation (1) for each trajectory.

$$(1) \quad \text{STL} = -\ln(\text{prob}(z)) \text{ with } z = \frac{(E - E_r)}{\sigma E_r}$$

where  $E$  is a measure the diversity of neighboring data points on the trajectory in the reconstructed state space.  $E$  can become zero for a completely deterministic (e.g. constant) signal, but cannot become arbitrarily small on average for a system with a stochastic content.  $E_r$  (and its variance  $\sigma E_r$ ) are obtained by calculating  $E$  for a number of surrogate replications of the original data in such a way that the score  $z$  tests against the null hypothesis that the data measured is linearly-autocorrelated, stationary Gaussian noise observed through a static, nonlinear transform. Thus, STL is a measure of the determinism of the brain, defined locally for each channel, subject and trial (which group according to conditions of interest).

3) Compute a measure STG (STate Global) for each subject and trial by collapsing STL over all channels using equation (2)

$$(2) \quad \text{STG} = -\ln(\text{prob}(\chi^2)) \text{ with } \chi^2 = 2 \sum_{i=1}^N \text{STL}_i$$



where  $N$  denotes the number of recording channels. Thus, STG is a measure of the (pre-stimulus) determinism of the brain, defined for each subject and trial. From a neurophysiological perspective, determinism as measured by STG implies that the dynamic behavior - the totality of electrophysiological processes observed macroscopically - of a neural system is ordered, stable, and predictable to some extent. This determinism measure then can be used to describe the endogenous brain state at any given point in time (i.e. as more or less deterministic). Of course, many other variables could be captured (e.g. the amplitude of the endogenous signal) to describe different aspects of endogenous activity. However, we believe that the determinism measure is of significant import for many research topics of relevance to management and organizations. Briefly, in a conceptual sense, determinism in the neuronal (pre-stimulus) response can be argued to be highly relevant to conceptualization of free will, and thus choice and decision. It is beyond the scope of this section to go into details, but it suffices to say that some scholars view nonlinear dynamic system theory as an operational means to define free will, in a way that allows one to reconcile free will with determinism (Ridley, 2003). The system is deterministic, but still by no mechanism can you definitively say what the system is going to do next. In a sense then, it is argued that this unpredictable behavior provides the illusion of free will, which, in words of Wilson (1998) "... would seem to be free will enough to drive human progress and offer happiness ...".

## **TAKING ACCOUNT OF ENDOGENOUS BRAIN ACTIVITY IN ORGANIZATIONAL RESEARCH**

In this section, we build on the more technical introductions above to define a series of applications in organizational and management research where an incorporation of endogenous brain activity both in theory development and empirical testing may lead to substantive advances

in knowledge. Our intention is not however to exhaust all possible avenues where EBA may be of significant use, but rather to provide a set of useful examples, that should inspire readers to think about the utility of incorporating EBA in their own research topics. At this point though, we would like to sound a note of caution. Specifically, we do not wish to inspire what might be most kindly termed exploratory, atheoretical, ‘fishing expeditions’ by researchers. It is vital that work incorporating EBA and related concepts is strongly theory-driven. Specifically, we urge researchers to avoid simply looking for observed correlations between EBA and organizational activities or decisions. Such an approach is likely of course to lead to some observed findings, but the scientific value of such findings is highly questionable. Rather, researchers should first develop deep theoretical understandings of how EBA is likely to influence organizational decisions and behaviors, develop strong hypotheses, and only then proceed to empirical work.

We begin with an overview of an existing example of an organizationally-relevant study which incorporated EBA, with the intention of setting the scene, and also translating the possibly rather abstract idea of EBA and pre-stimulus brain states into a concrete business-relevant context. Further, we will show how the general principles uncovered by this particular study can be extended to many other organizational and management contexts. In essence then, we move from the specific to the general, in a step-by-step process that should help readers apply EBA to their own topics.

Specifically, Braeutigam (2007) drew from theories regarding preference construction (e.g. Bettman, Luce, & Payne, 1998) to develop a study which measured the impact of EBA on decision making in 16 subjects, across a total of 90 different choice-inducing stimuli in a simulated shopping trip, using Magnetoencephalography (MEG). The measurements of EBA were in line with those already outlined in Section 3 of the present paper – that is, a measure of

the determinism of the pre-stimulus brain signal, with the sample split into high and low determinism groups. A significant difference was observed across the two groups, with those choices made when the subject exhibited a highly deterministic pre-stimulus brain state (i.e. before the choice stimuli were presented) making significantly quicker choices, and also choosing significantly less familiar items than those in the low determinism pre-stimulus state. As such, the endogenous brain activity (that is, brain activity before the choice options were presented) explained significant amounts of variance in the actual choices that were made. To put it another way, one could predict the future choice of the subject (in terms of the familiarity of the product), *before* that subject even saw the choice options, by observing their EBA. Given that it appears to be relatively well established that our EBA is constantly fluctuating between higher and lower deterministic states (see Braeutigam and Swithenby, 2003), the finding that our EBA seems to bias our decision making towards more or less familiar choice outcomes is significant.

While Braeutigam (2007) expressly referred to existing theories on consumer preference construction, research in that area is almost entirely behavioral in nature, and considerably less attention is given to the psychological and / or neurobiological underpinnings of preference construction (CITE). Incorporating EBA into work in the area is thus likely to provide significant insight into human decision making, preference, and choice. For example, in a face recognition context Braeutigam and Swithenby (2003) suggest that high determinism pre-states may signify a kind of ordered anticipatory state, where the brain may be anticipating making some decision and is preparing templates and pathways for the anticipated recognition task. Conversely, low determinism pre-states may be a less anticipatory, and more unordered, state. Braeutigam and Swithenby (2003) reported that low pre-states exhibited rapid activity in facial recognition areas,

presumably as the brain quickly activated those areas needed for the unanticipated situation, while those in high pre-states did not exhibit the same activity, presumably because they were already in an anticipatory state. Applying this reasoning to the Braeutigam's (2007) study, it may be that a highly deterministic pre-state may signify some kind of preparation for or anticipation of a decision-task, which is supported Braeutigam's (2007) finding that these high pre-state subjects also exhibited high activity in brain areas associated with evaluation of reward (orbito-frontal and parietal cortices). Building on this, individuals in high determinism pre-states could be considered as more prepared to choose unfamiliar outcomes, and then to evaluate the rewards / costs of those choices. In other words, they are better prepared for what amounts essentially to a learning activity. Conversely, those in low pre-states are less capable of doing this, and tend towards the familiar (which has no novel learning opportunity). It is important to note however, that this 'learning capability' is seen here as a dynamic quality rather than person-specific trait.

Indeed, the integration of EBA into organizational theory looks likely to extend our knowledge quite substantively. While it would be reasonably easy to speculate rather widely, in our view this would be counterproductive, and thus we restrict our general discussion to fields in which we believe researchers can most clearly derive testable hypotheses at this point. Specifically, we believe that the fields of organizational study that will find most benefit from understanding EBA at present are those concerned with choices and decisions, and particularly when involving risk. Of course, the Braeutigam (2007) example above was in a consumer-specific context, and it can be easily seen how EBA can play a major role here. However, many fields of study relevant to management and organizations involve judgments, choices, preferences, decisions, and risk.

It is not possible to give details on every single possible area of application for EBA in organizational research, and we would expect many readers to naturally fit their own specific areas of interest to our more general ideas here. However, we can provide a more detailed illustration of the potential of EBA to inform organizational research by using as a context a topic that has proven to be both popular within general organizational research, and also with those employing neuroscientific methods; entrepreneurship. A stream of research has recently developed that purports to show differences in brain functioning between highly entrepreneurial individuals, and those lower in entrepreneurship (Lawrence et al., 2008; Nicolaou et al., 2008). Studies have suggested that highly entrepreneurial people differ in terms of the structure of the reward centers in the brain, which somehow predisposes them towards risk-seeking behavior during particular circumstances relevant to entrepreneurship (i.e. high-stakes opportunities, which as a result contain high levels of potential affect). As such, authors such as Becker, Cropanzano and Sanfey (2011) suggest that successful entrepreneurs can be identified by examining their brain structure, and even that it is feasible to use neurochemical-altering drugs to increase entrepreneurial behavior (Lawrence et al., 2008). Such work has been strongly criticized in a number of quarters, as overly reductionist, ignoring the complexities of organizational and human life, and even as being somewhat questionable, being as it looks to categorize employees and perhaps advocates developing them using neuroscientific means (e.g. Lindebaum and Zundel, 2013).

Incorporating a dynamic perspective based around EBA can help extend our growing knowledge of how individuals may make entrepreneurial decisions, and in doing so also respond to existing criticisms of neuroscientific work within organizations (e.g. Lindebaum, 2016), and also to. Specifically, we have shown above that the determinism (high or low) of an individual's

intrinsic brain activity, even before they are presented with a choice, has a substantive impact on the level of risk inherent in the choice they will make in the future. Further, we also know that these endogenous brain states fluctuate dynamically in all individuals, so that any given 'potential entrepreneur' say, could be in either a high or low deterministic pre-state at any given time. Thus, rather than classify subjects into stable and defined 'high' and 'low' type entrepreneurial groups by way of their brain structure and neurochemistry, it is probably more accurate to explore the dynamic impact of pre-stimulus brain states on entrepreneurial decisions over time. In other words, if we are in the right endogenous brain state, any of us could exhibit (at least to some extent) high-type entrepreneurial activity. This makes it very questionable to classify individuals (as for example high or low-type entrepreneurs) at the neuroanatomical level, since EBA fluctuations would ensure that any individual at the right time could be (in this example) highly entrepreneurial.

The example above illustrates how incorporating EBA in neuroscience-based organizational research leads to a very important difference in approach from much existing organizational research. Specifically, understanding EBA requires that we move beyond looking for concrete and time-invariant differences between individuals based on brain structure or activity, and using these to classify them into stable groups, and instead move towards a dynamic understanding that any individual may have the potential to choose or act in a given way at a given time, dependent on fluctuations in their EBA. As alluded to above, this is one way that organizational researchers who wish to apply neuroscientific techniques and theories can respond to recent criticism of organizational neuroscience as primarily based on unrealistic and naïve reductionist classification of individuals, ignorant of social and organizational context (e.g. Lindebaum, 2016; Lindebaum and Zundel, 2013).

It can be seen that EBA looks to be a powerful addition to theories on choice-making under risky conditions, a context relevant to many management and organizational topics beyond entrepreneurship and consumer behavior. For example, stock market investment, recruitment, incentivization and many other decisions involve trading off more or less risky options. However, beyond risk, incorporating an understanding of EBA also sheds light on the topic of judgment, choice, and decisions in general. Within this broad context, we will focus here on the overarching concept of preference construction. More specifically, in recent years, it has become progressively more accepted that individuals do not make decisions and choices in a way that suggests they adhere to rational decision rules such as utility maximization (Lichtenstein and Slovic, 2006). Indeed, it is increasingly questionable whether it is viable to consider that individuals even have stable preferences, and more likely that many of our preferences are at least in part constructed during the process of elicitation (Kahneman & Tversky, 2000). Research in this area has often relied on changes in the framing of the decision options to exhibit differences across individuals in the actual decision. For example, it is well established that more individuals will prefer something (e.g. organ donation) if it is framed as an opt-out rather than an opt-in (Johnson and Goldstein, 2006), even though the choice itself is exactly the same. This, and many other examples, are generally considered as decision biases, where humans make non-rational decisions in response to changed contextual factors or decision framing (e.g. loss versus gain frames). However, research in this area has primarily taken a behavioral approach, rather than attempt to understand *why* we are subject to these so-called biases, other than some evolutionary or information processing limitation explanations (CITE). We however suggest that fluctuations in EBA may also play some role in the choice-making process. Indeed, interpreting the determinism of the endogenous brain state as essentially the brain's predictive mechanism,

biasing us towards the task of making one or another type of choice, or responding to particular anticipated types of information (e.g. faces), sheds significant light on the possible reasons why humans may exhibit what are currently seen as behavioral decision biases, and as constructed rather than stable preferences.

We have already referred to research showing that the endogenous brain state has a significant impact on future choice, even before the choice options are presented, in terms of risk taken. However, it remains in question whether this is driven by the *actual* risk inherent to the choice option (e.g. investing in an actually more risky venture with greater payoffs), or whether EBA somehow influences an individual's *perception* of risk. This could be tested by combining measurements of EBA with the use of paradigms common in preference construction research, such as perhaps equally risky choices that are framed in different ways. Further, given that Braeutigam (2007) shows significant activity in reward evaluation brain areas after subjects in high-determinism pre-states made more risky choices, we could theorize that high-determinism pre-states could bias the individual *towards* gain-framed choices, rather than *avoiding*-loss frames. Another theoretical framework can be incorporated here however, concerning perception itself. Existing work shows that EBA is associated with differences in the perception of ambiguous stimuli such as Rubin's face-vase figure (see section 2). It could be that pre-choice brain states could somehow influence the actual perception of the choice options themselves in some way, rather than the evaluation of their risk / reward. Such research would however require considerable effort to frame theoretical hypotheses which usefully incorporate strands from both neuroscience, and behavioral economics. However, such efforts are likely to be extremely worthwhile.



In this sense then, incorporating EBA into models of judgment, choice and decision, allows a further layer of understanding on how humans make decisions in key organizational and economic contexts. In particular, we take the point of explanation one step further back, to before the choice options have even been presented to the individual. This may indeed help explain variability in choice making (see section 2 of this paper also), and preference construction, but also presents an even stronger hypothesis. Specifically, it may be that a substantive part of our exhibited preference (i.e. our choice) may be influenced even *before* we see the choices available to us. This may at the least narrow down our possible choice space, even if it does not entirely predetermine it. Although perhaps not immediately obvious from an applied organizational angle, it is important at this point to raise again the notion of free will. From a neuroscience perspective, the question of free will gained momentum after the discovery of the so-called readiness potential, which is a (kind of state) measure of activity in the brain's motor area leading up to voluntary muscle movement. Critically, the potential can be measured about 0.4 seconds before the subject's conscious awareness of 'desiring to make a movement', raising questions about to which extent volition is actually free (Kornhuber & Deecke, 1990).

From a philosophical perspective, Nagel (1987) gives a concise introduction to the question of free will, in the end coming to the conclusion that it depends on an untenable assumption that one could in principle have made a different choice at any given point in time (see also Dennett, 2003 for further discussion). For example, to take the current context of one of the present authors, is it really feasible that if he was sent back in time 20 minutes, he could have ordered a single malt rather than a bourbon? Nagel suggests that, while he may imagine he 'could have' chosen differently, this is in fact an illusion. Rather, every single act, influence, and decision taken prior to that instant was leading up to that particular decision to choose bourbon.

As such, it is illusory to believe that there could have been a different choice made, without there being some different influence, making the idea of free will as we understand it untenable. This view would be broadly in line with Lloyd's recent work, suggesting that the impression of free will is caused by the intrinsic computational unpredictability (as evidenced by the halting problem<sup>1</sup> for example) underlying any decision-making process (Lloyd, 2012).

As mentioned already, fluctuations in our intrinsic brain activity could be taken to represent some notion of practical free will in a deterministic world, given that these fluctuations seem to influence our choices. However, a different interpretation would be that taking in hand the influence of EBA on choice casts further doubt on commonsense understandings of free will. More specifically, we have already established herein that a substantive component of our choice making is dependent on a fluctuating intrinsic brain activity, which we cannot ourselves apprehend nor therefore control (although see the subsequent discussion of neurofeedback for further reflection on this). Taken together with the preference construction literature, we must surely now abandon the idea that decision making is simply an act of freely choosing the outcome that will maximize some utility function based on stable pre-existing preferences. Acceptance of this has significant implications both for how we direct future research efforts on individual human behavior, as well as that in organizations, and society in general.

In this light, it is questionable whether current applications of neuroscience to management and organizational research are proceeding in the most insightful manner. Certainly, it seems to us that an approach concerned with uncovering stable and general neurobiological differences between managers (for example), and further then classifying them into 'types' (as for example in the entrepreneurship example discussed earlier), is probably lacking in its ability to really explain variation in behavior, performance, and the like. Such

observed differences may in fact be little more than chimera when intrinsic brain activity is taken into account as an influence on choice and behavior. Similarly, purely event-based experimental designs themselves - which all existing neuroscientific research in management and organizations consists of - are likely to be ignoring a critical confound at best, and a key explanatory variable at worst. We are of course just at the beginning of understanding the influence of EBA on management and organizational behavior, and how to incorporate these dynamic brain state changes into existing research. However, EBA-based thinking clearly moves beyond the simplistic reductionist and classification approaches criticized by those such as Lindebaum (2016; Lindebaum and Zundel, 2013). Indeed, ignoring intrinsic brain activity in our models would seem to be a significant failing for future neuroscientific work in management and organizations. That said, the application of EBA to organizational practice may be seen to be less clear. Specifically, if managers do not know what brain state they are in, how can knowledge of its influence impact on making better organizational practice? This is a challenging issue. However, recent work in the area of neurofeedback may offer the beginnings of a solution.

## **5. FROM NEUROFEEDBACK TO NEUROFEEDFORWARD: AN ENDOGENOUS BRAIN ACTIVITY PERSPECTIVE**

Neurofeedback is a psychophysiological technique in which participants are shown displays of their cortical activity in order to reinforce a subsequent pattern of brain activation in a self-regulatory fashion (Hammond, 2005, 2011). In essence, with visibility of the neural activity, individuals can learn to control it (somewhat akin to learning to wiggle one's ears with the help of a video camera to observe them). This form of biofeedback has been traditionally used with EEG, (Light et al, 2010), although the field is rapidly evolving and other neuroimaging techniques such as fMRI and MEG are now being advocated (Foldes, Vinjamuri, Wang, Weber

& Collinger, 2011). The neurofeedback paradigm exploits cortical plasticity and learning by modulating brain activity in response to an external stimulus (e.g., a pleasant picture, or suchlike). The accepted rationale is that by modulating the activity at the cortical level, neurofeedback training can by extension modulate subsequent behavior (e.g., Gruzelier, 2014a, 2014b). The implication is that by repeating such training over a period of time, the cortical response would become trained to respond to specific stimuli and then adapt the pattern of responses, and subsequent behavior, to subsequent presentations of that particular stimulus (Bagdasaryan & Quyen, 2013; but see Massaro, 2015). Thus, neurofeedback is effectively operant conditioning at a cortical level.

Needless to say such an approach has immediate and obvious implications for clinical therapy, and indeed neurofeedback paradigms are applied to such regimes as a matter of standard practice, with patients suffering from conditions such as anxiety and depression benefiting (Serman, 2000; Moore, 2000). Further, Waldman, Balthazard, and Peterson (2011) suggest neurofeedback could be an effective tool for management training. Indeed, various studies have shown that cognitive skills can be improved with neurofeedback focusing on alpha band [8-12Hz] activity, which is thought to play a role in inhibition of distracting information (Vernon et al, 2003; Vernon, 2005). Mental skills that would play a role in effective management behavior, such as cognitive control, mental manipulation and even task attention, have all been seen to show a significant improvement with alpha band neurofeedback (Hanslmayr et al, 2005; Vernon et al, 2003; Lubar, 1991; 1997; 2003). However, it is as a means to examine and modulate the intrinsic neuronal state (i.e. EBA) that neurofeedback has best utility to inform an understanding of our organizational behaviors, and possibly increase their effectiveness. In this sense, given that EBA is a pre-stimulus brain state, the more accurate term may actually be *neurofeedforward*.

The idea of neurofeedforward, which we develop here, is an extension of existing neurofeedback paradigms to include an adaptive element, where the precise nature of the upcoming stimulus is decided upon based on the momentary brain state. Neurofeedforward would involve continuous measurement of EBA, and a consequent modification of the stimulus presented to the subject, based on the EBA state. We will give a brief example of how this may be used in practice in due course. However, first we cover the basic details of which neural activity may be of most relevance. First, recall from section 2 of the present paper that research into EBA has focused on pre-stimulus brain activity in the theta [4-7Hz], alpha [8-12Hz] and beta [13-30Hz] bands. For effective organizational behavior it would seem that neurofeedforward training that modulates the endogenous alpha activity would be the most obvious choice in the first instance. For example, recent work has shown that endogenous coherence in the alpha band window predicts the subsequent outcome of an individual's decision in an ultimatum game (Billeke, Zamorano, Cosmelli and Aboitiz, 2013). Further, later work from the same laboratory showed that such predictive value is evident only when the individual thought they were interacting with a human as opposed to a computer (Billeke, Zamorano, Chavez, Cosmelli, and Aboitiz 2014).

The study of modulation of EBA in the beta and theta frequency windows also lends possible insight into the understanding of effective organizational behaviors. For example, the ability to decide not to proceed with a particular choice has been shown to be predicted by modulations in endogenous beta coherence with a pattern of decreasing and increasing coherence in this frequency window suggesting that each potential outcome was considered prior to deciding not to respond (Gluth, Rieskamp & Buchel, 2013). Here it seems that neurofeedforward paradigms may have particular utility, as it has already been shown that modulation of

endogenous brain activity in the beta frequency window leads to an improvement in social facets such as familiarity (Keizer, Verment & Hommel, 2010), and in driving decisions that that are driven by positive memories (Zotey, Phillips, Yuan, Misaki & Bodurka, 2014). While further work has shown that the relationship between increases in theta band power and subsequent recall of an event is mediated by the degree of intention to recall and not the ability to recall per se (Schneider & Rose, 2016). In addition further studies have revealed that targeted protocols that have focused on pre-stimulus levels of theta power have shown a concomitant increase in recall in target events (Vernon et al, 2003).

To show how neurofeedforward may work in practice, we return here to the leadership example given at the very beginning of this paper. It can be seen that in most cases, any decisions to be made about the implementation of organizational change involve some level of risk, whether these be financial, performance-related, social, or many others. Neurofeedforward-based training may help leaders to cope with such risks by augmenting their ability to make the ‘correct’ decisions in such circumstances. How would this work? First, consider that existing research already suggests that individuals in low-determinism endogenous brain states are more likely to choose more familiar alternatives (i.e. less risky / more conservative decisions, see Braeutigam, 2007). Thus, it would for example be possible to present those in low-type EBA states with a choice set where the optimal choice would be the less conservative / more risky option. It is anticipated that in doing so, over time we would be able to train individuals (such as leaders) to recognize the potential ‘biases’ caused by their high/low-type EBA state, and in doing so make better decisions. The objective is not thus to learn to ‘control’ one’s EBA, but to instead learn to take account of it in decision making.

## **6. CONCLUSIONS**

In this paper, we have introduced the important idea of endogenous brain activity to management and organizational research. This intrinsic brain activity goes beyond that which is necessary to keep our bodies functioning, and its study, and incorporation into theories and empirical work, has many important consequences for management and organizational research. Certainly, it is now well accepted in neuroscience that endogenous brain activity, typically conceptualized as the pre-stimulus brain state, explains a substantive amount of variance in stimuli responses. Further, stimulus-driven brain activity does not simply add to or suppress pre-stimulus activity, the latter instead interacts in a non-linear way with incoming information (Sadaghiani and Kleinschmidt, 2013). This makes completely untangling endogenous brain activity fluctuations from stimuli-driven activity virtually impossible, and further necessitates its consideration in our models.

Taking account of endogenous brain activity has the potential to revolutionize both our understanding of how we make choices and behave in organizational settings, and also how we go about theorizing about and investigating such issues. To this end, we have provided a conceptual and technical introduction to thinking about and measuring endogenous brain activity, in the form of the determinism of the signal. Prior work suggests that this pre-stimulus determinism measure is associated with important post-stimulus effects (e.g. Braeutigam, 2007), and as such, can be thought of to predict the subsequent decisions to some extent. In light of this, we gave a number of specific and general ideas of how pre-stimulus brain states may be of significant impact in management and organizational research fields. We spent much of this effort on elucidating the impact of EBA on contexts relevant to choice, risk, decisions, and the like, where it is evident that incorporating EBA into research here has substantial utility.

The notion of intrinsic brain activity however has significant import for a number of much more fundamental aspects of how we think about our brain, and its importance to management and organizational research. In particular, the approach to research suggested herein extends Senior, Lee, and Butler's (2011) organizational cognitive neuroscience approach, and helps to counter criticisms of neuroscience in organizational research levied by authors such as Lindebaum and Zundel (2013). More specifically, much of the latter authors' criticism revolves around the basic reductionist idea of isolating specific management or organizational concepts (e.g. leadership) within specific parts of the brain. Recognizing the key influence of the brain's ongoing endogenous activity provides one way to navigate around these issues. More specifically, we have demonstrated that EBA is best thought of as a whole-brain, dynamically fluctuating brain state, which interacts in a complex non-linear way with stimulus-evoked activity in a given area or network. As such, we move beyond the reasonably simplistic reductionism cited in Lindebaum and Zundel (2013), towards a dynamic, complex-systems based model. Further, the intrinsic view, as opposed to the reactive view, tends to draw focus away from the categorization of individuals into groups based on neuroanatomical structure or functional brain activity associated with a given organizational behavior or performance measure, another important criticism implied by prior commentators (e.g. Lindebaum & Zundel, 2013; Lindebaum, 2016). Indeed, Healey and Hodgkinson (2014, p. 6), although they criticize Lindebaum and Zundel's (2013) position, also criticize the localization of function approach to neuroscience in management and organizations. Rather, they suggest that it is better to consider the interplay of multiple distributed regions and structures (i.e., neuronal dynamics) in producing higher-order cognitions, affects, and functions. We concur, but also add to this framework by including consideration of whole-brain dynamic intrinsic activity (measured in this case using



determinism), which does not reduce to isolated components associated with specific tasks or responses.

Further, accepting the important role of EBA allows us to question our notions of how our brain primarily works. Rather than being a reactive engine, waiting for some stimulus to respond to – the primary assumption of almost all current experimental neuroscience and psychology (including that applied to management and organizations) – it could be that the brain is, to a significant extent, a predictive inference engine. In other words, EBA facilitates the prediction of future demands and stimuli from the environment, helping prepare the brain to respond most effectively to what it ‘guesses’ may occur in the future. In this sense, the brain would work similarly to a Bayesian inference engine (e.g. Knill and Pouget, 2004), where EBA in some ways represents our ‘priors’, or guesses, about the environment, which are then updated by experience. This would tally with the findings reported in a number of EBA studies (e.g. Braeutigam and Swithenby, 2003; Braeutigam, 2007).

Of course, we do not expect this paper to precipitate a wholesale revolution in organizational science in general, or even for those working with neuroscience in such fields. Many researchers will likely continue to devote their efforts to event-based experiments based around a reactive view of evoked brain activity and / or cognition. However, as pointed out by Raichle and Snyder (2007, p. 1087): “such a limited approach will eventually be exhausted if not nourished by a broader consideration and understanding of the relevant neurobiology. What is required is an expanded framework upon which to base such a research agenda. Neuroscience and the behavioral sciences together must provide that framework”. We fully support this view, indeed, taking in hand the future directions presented in the present paper, we believe that it is by incorporating an understanding of EBA into research tasks and problems from management and

organizational research (as well as general behavioral science) that we can develop a more accurate view of how our brain works to support our path through life. Or, understand how we anticipate our ‘collisions with the future’.

## **FOOTNOTES**

1. The halting problem concerns the determination of whether a Turing machine (a theoretical computing machine serving as an idealized model for mathematical calculation) will eventually come to a halt given an input program. The halting problem is solvable for sufficiently simple machines. As first proved by Turing himself, however, the problem of whether a general Turing machine will come to a halt is not decidable.

## REFERENCES

- Addante, R.J., Watrous, A.J., Yonelinas, A.P., Ekstrom, A.D. & Ranganath, C. (2011). prestimulus theta activity predicts correct source memory retrieval. *Proceedings of the National Academy of Sciences of the United States of America*, 108(26):10702–10707.
- Ai, L. & Ro, T. (2014). The phase of prestimulus alpha oscillations affects tactile perception. *Journal of Neurophysiology*, 111:1300–1307.
- Bagdasaryan, J. and Quyen, M.L.V. (2013). Experiencing your brain: neurofeedback as a new bridge between neuroscience and phenomenology. *Frontiers in Human Neuroscience*, 7(680): 1-10: doi: 10.3389/fnhum.2013.00680.
- Bechtel, W. and Abrahamsen, A. (2010). Dynamic mechanistic explanation: computational modeling of circadian rhythms as an exemplar for cognitive science. *Studies in History and Philosophy of Science Part A*, 41(3):321-333.
- Bechtel, W. and Abrahamsen, A. (2010). Dynamic mechanistic explanation: computational modeling of circadian rhythms as an exemplar for cognitive science. *Studies in History and Philosophy of Science Part A*, 41(3): 321-333.
- Becker, W. J., Cropanzano, R. and Sanfey, A. G. (2011). Organizational neuroscience: Taking organizational theory inside the neural black box. *Journal of Management*, 37(4): 933-961.
- Bernasconi, F., Manuel, A.L., Murray, M.M. & Spierer, L. (2011). Pre-stimulus beta oscillations within left posterior sylvian regions impact auditory temporal order judgment accuracy. *International Journal of Psychophysiology*, 79:244–248.
- Bertuglia, C.S. & Vaio, F. (2005). *Nonlinearity, Chaos and Complexity*. Oxford University Press, Oxford, UK.
- Billeke, P., Zamorano, F., Chavez, M., Cosmelli, D. and Aboitiz, F. (2014). Functional cortical network in alpha band correlates with social bargaining. *PLOS One*, 9(10): e109829. doi: 10.1371/journal.pone.0109829. eCollection 2014.
- Billeke, P., Zamorano, F., Cosmelli, D. and Aboitiz, F. (2013). Oscillatory brain activity correlates with risk perception and predicts social decisions. *Cerebral Cortex*, 23(12): 2872-2883.
- Biswal, B. B. (2012). Resting state fMRI: A personal history. *Neuroimage*, 62(2): 938-944.
- Bompas, A., Sumner, P., Muthumumaraswamy, S.D., Singh, K.D. & Gilchrist, I.D. (2015). The contribution of pre-stimulus neural oscillatory activity to spontaneous response time variability. *NeuroImage*, 107:34–45.
- Boyatzis, R.E., Rochford, K. & Jack, A.I. (2014). Antagonistic neural networks underlying differentiated leadership roles. *Frontiers in Human Neuroscience*, 8(Article 114):1-15.

- Braeutigam, S. (2007). Endogenous context for choice making: A magnetoencephalographic study. In *International Congress Series* (Vol. 1300, pp. 703-706). Elsevier.
- Braeutigam, S. and Swithenby, S. J. (2003). Endogenous context for visual processing of human faces and other objects. *NeuroReport*, 14(10):1385-1389.
- Busenitz, L. and Barney, J. B. (1997). Differences between entrepreneurs and managers in large organizations: Biases and heuristics in strategic decision-making. *Journal of Business Venturing*, 12(1): 9–30.
- Chaumon, M. & Busch, N.A. (2014). Prestimulus Neural Oscillations Inhibit Visual Perception via Modulation of Response Gain. *Journal of Cognitive Neuroscience*, 26(11):2514–2529.
- Choi, Y. R. and Shepherd, D. A. (2004). Entrepreneurs' decisions to exploit opportunities. *Journal of Management*, 30(3): 377-395.
- Cole, M.W., Reynolds, J.R., Power, J.D., Repovs, G., Anticevic, A. and Braver, T. (2013). Multi-task connectivity reveals flexible hubs for adaptive task control. *Nature Neuroscience*, 16(9): 1348-1355.
- Damoiseaux, J. S., Rombouts, S., Barkhof, F., Scheltens, P., Stam, C. J., Smith, S. M. and Beckmann, C.F. (2006). Consistent resting-state networks across healthy subjects. *Proceedings of the National Academy of Sciences of the United States of America*, 103(37): 13848-13853.
- Dennett, D. (2003). *Freedom evolves*. London: Allen Lane Books.
- Dumas, G., Nadel, J., Soussignan, R., Martinerie, J. and Garnero, L. (2010). Inter-Brain Synchronization during Social Interaction. *PLoS ONE*, 5(8): e12166. doi:10.1371/journal.pone.0012166.
- Faust, O. & Bairy, M.G. (2012). Nonlinear analysis of physiological signals: a review. *Journal of mechanics and medicine in biology*, 12(4):320-331.
- Fawcett, I., Hillebrand, A. and Singh, K. D. (2007). Several sequence of evoked and induced cortical responses to implied motion processing in human motion area V5/MT+. *European Journal of Neuroscience*, 26(3): 775–783.
- Foldes, S.T., Vinjamuri, R.K., Wang, W., Weber, D.J., and Collinger, J.L. (2011). Stability of MEG for Real-Time Neurofeedback. Engineering in Medicine and Biology Society, EMBC. *Proceedings of the Annual International Conference of the IEEE*, 5778 - 5781.
- Fox, M. D., Snyder, A. Z., Vincent, J. L., Corbetta, M., Van Essen, D. C., and Raichle, M. E. (2005). The human brain is intrinsically organized into dynamic anticorrelated functional networks. *Proceedings of the National Academy of Sciences of the United States of America*, 102(27): 9673-9678.
- Fox, M.D, and Raichle, M.E. (2007). Spontaneous fluctuations in brain activity observed with

- functional magnetic resonance imaging. *Nature Reviews: Neuroscience*, 8(9):700-711.
- Freyd, J.J. (1983). The mental representation of movement when static stimuli are viewed. *Perception & Psychophysics*, 33(6): 575-581.
- Geerligs, L. Akyürek, E.G. (2012). Temporal integration depends on increased prestimulus beta band power. *Psychophysiology*, 49:1464–1467.
- Gluth, S., Rieskamp, J., and Büchel, C. (2013). Deciding not to decide: computational and neural evidence for hidden behavior in sequential choice. *PLoS Computational Biology*, 9(10): e1003309.
- Gruzelier, J.H. (2014a). EEG-neurofeedback for optimising performance. I. A review of cognitive and affective outcome in healthy participants. *Neuroscience and Biobehavioural Reviews*, 44(7): 124–141.
- Gruzelier, J.H. (2014b). EEG-neurofeedback for optimising performance. II: creativity, the performing arts and ecological validity. *Neuroscience and Biobehavioral Reviews*, 44(7):142–158.
- Hammond, D.C (2011). What is Neurofeedback: An Update. *Journal of Neurotherapy: Investigations in Neuromodulation, Neurofeedback and Applied Neuroscience*, 15(4): 305-336.
- Hammond, D.C. (2005). Neurofeedback Treatment of Depression and Anxiety. *Journal of Adult Development*, 12(2/3): 131-137.
- Hannah, S., Schaubroeck, J. M. and Peng, A. C. (2015). Transforming followers' value internalization and role self-efficacy: Dual processes promoting performance and peer norm-enforcement. *Journal of Applied Psychology*, 101(2): 252-266.
- Hanslmayr, S., Sauseng, P., Doppelmayr, M., Schabus, M., and Klimesch, W. (2005). Increasing individual upper alpha power by neurofeedback improves cognitive performance in human subjects. *Applied Psychophysiology and Biofeedback*, 30(1): 1-10.
- Hanslmayr, S., Volberg, G., Wimber, M., Dalal, S.S. & Greenlee, M.W. (2013). Prestimulus Oscillatory Phase at 7 Hz Gates Cortical Information Flow and Visual Perception. *Current Biology*, 23:2273–2278.
- Hesselmann, G., Kell, C.A, Eger, E. & Kleinschmidt, A. (2008). Spontaneous local variations in ongoing neural activity bias perceptual decisions. *Proceedings of the National Academy of Sciences of the United States of America*, 105(31): 10984–10989.
- Hilborn, R. (2004). Sea gulls, butterflies and grass shoppers: a brief history of the butterfly effect in nonlinear dynamics. *American Journal of Physics*, 72(4): 425-427.
- Horgan, J. (1995). From Complexity to Perplexity. *Scientific American*, June.

- Huang, Z., Zhang, J., Longtin, A., Dumont, G., Duncan, N.W., Pokorný, J., Qin, P., Dai, R., Ferri, F., Weng, X. & Northoff, G. (2015). Is There a Nonadditive Interaction Between Spontaneous and Evoked Activity? Phase-Dependence and Its Relation to the Temporal Structure of Scale-Free Brain Activity. *Cerebral Cortex*, 1–23.
- Johnson, E. J. and Goldstein, D. G. (2006). Do defaults save lives? In Lichtenstein, S. and Slovic, P., editors, *The Construction of Preference*, pp. 682-688. Cambridge University Press: Cambridge, UK.
- Kahneman, D. and Tversky, A. (2000). *Choices, Values, and Frames*. Cambridge University Press: Cambridge, UK.
- Keil, J., Müller, N., Hartmann, T. & Weisz, N. (2014). Prestimulus Beta Power and Phase Synchrony Influence the Sound-Induced Flash Illusion. *Cerebral Cortex*, 24:1278–1288.
- Keil, J., Müller, N., Ihssen, N. & Weisz, N. (2012). On the Variability of the McGurk Effect: Audiovisual Integration Depends on Prestimulus Brain States. *Cerebral Cortex*, 22:221-231.
- Keizer, A.W., Verschoor, M., Verment, R.S. and Hommel, B. (2010). The effect of gamma enhancing neurofeedback on the control of feature bindings and intelligence measures. *International Journal of Psychophysiology*, 75(1): 25-32.
- Knill, D. C. and Pouget, A. (2004). The bayesian brain: the role of uncertainty in neural coding and computation. *Trends in Neurosciences*, 27(12):712-719.
- Kornhuber, H.H., & Deecke, L. (1990). Readiness for movement - the Bereitschaftspotential story. *Current Contents Clinical Medicine*, 18(4): 14.
- Lange, L., Halacz, J., van Dijk, H., Kahlbrock, N. & Schnitzler, A. (2012). Fluctuations of Prestimulus Oscillatory Power Predict Subjective Perception of Tactile Simultaneity. *Cerebral Cortex*, 22:2564– 2574.
- Lawrence, A., Clark, L., Labuzetta, J. N., Sahakian, B., and Vyakarnum, S. (2008). The innovative brain. *Nature*, 456(7219):168-169.
- Lewis, C.M., Baldassarre, A., Committeri, G., Romani, G.L. & Corbetta, M. (2009). Learning sculpts the spontaneous activity of the resting human brain. *Proceedings of the National Academy of Sciences of the United States of America*, 106(41):17558-17563.
- Lichtenstein, S. and Slovic, P. (2006). The construction of preference: An overview. In Lichtenstein, S. and Slovic, P., editors, *The Construction of Preference*, pp. 1-41. Cambridge University Press: Cambridge, UK.
- Light, G.A., Williams, L.E., Minow, F., Sprock, J., Rissling, A., Sharp, R., Swerdlow, N.R., and Braff, D.L. (2010). Electroencephalography (EEG) and Event-Related Potentials (ERP's) with Human Participants. *Current Protocols in Neuroscience*. 52(6):1–6.

- Lindebaum D. and Zundel M. (2013). Not quite a revolution: Scrutinizing organizational neuroscience in leadership studies. *Human Relations*, 66 (6): 857-877.
- Lindebaum. B. (2016). Critical Essay: Building new management theories on sound data? The case of neuroscience. *Human Relations*, 69(3): 537-550.
- Lloyd, S. (2012). A Turing test for free will. *Philosophical Transactions Royal Society A*, 370: 3597–3610.
- Lou, H. C., Joansson, M., Biermann-Ruben, K., Schnitzler, A., Østergaard, L., Kjaer, T. W., and Gross, J. (2011). Recurrent activity in higher order, modality Non-Specific brain regions: A granger causality analysis of autobiographic memory retrieval. *PLoS ONE*, 6(7):e22286+.
- Lubar, J. F. (1991). Discourse on the development of EEG diagnostics and biofeedback for attention-deficit/hyperactivity disorders. *Biofeedback and Self-regulation*, 16(3): 201-225.
- Lubar, J. F. (1997). Neocortical dynamics: implications for understanding the role of neurofeedback and related techniques for the enhancement of attention. *Applied Psychophysiology and Biofeedback*, 22(2): 111-126.
- Lubar, J.F., (2003). Neurofeedback for the management of attention-deficit disorders. In: Schwartz, M., Andrasik, F. (Eds.), *Biofeedback: A practitioner's guide*. The Guilford Press, New York, pp. 409–437.
- Massaro, S. (2015). Neurofeedback in the workplace: from neurorehabilitation hope to neuroleadership hype? *International Journal Of Rehabilitation Research*, 38 (3): 276-278.
- Mathewson, K.E., Gratton, G., Fabiani, M., Beck, D.M. & Ro, T. (2009). To See or Not to See: Prestimulus alpha Phase Predicts Visual Awareness. *The Journal of Neuroscience*, 29(9):2725–2732.
- Mennes, M., Kelly, C., Zuo, X. N., Di Martino, A., Biswal, B. B., Castellanos, F. X., and Milham, M. P. (2010). Inter-individual differences in resting-state functional connectivity predict task-induced BOLD activity. *Neuroimage*, 50(4): 1690-1701.
- Merkow, M.B., Burke, J.F., Stein, J.M. & Kahana, M.J. (2014). Prestimulus Theta in the Human Hippocampus Predicts Subsequent Recognition But Not Recall. *Hippocampus*, 24:1562–1569.
- Minkwitz, J., Trenner, M.U., Sander, C., Olbrich, S., Sheldrick, A.J., Schönknecht, P., Heger, U. & Himmerich, H. Prestimulus vigilance predicts response speed in an easy visual discrimination task. *Behavioral and Brain Functions*, 7:31-38.
- Moore, N. C. (2000). A review of EEG biofeedback treatment of anxiety disorders. *Clinical Electroencephalography*, 31(1): 1–6.
- Myers, N.E., Stokes, M.G., Walther, L. & Nobre, A.C. (2014). Oscillatory Brain State Predicts Variability in Working Memory. *The Journal of Neuroscience*, 34(23):7735–7743 .



- Nagel, T. (1987). *What Does it all Mean?* Oxford University Press: Oxford, UK.
- Nicolaou, N., Shane, S., Cherkas, L., Hunkin, J., and Spector, T. D. (2008). Is the tendency to engage in entrepreneurship genetic? *Management Science*, 54(1):167-179.
- Peateld, N., Mueller, N., Ruhnau, P., & Weisz, N. (2015). Rubin-vase illusion perception is predicted by prestimulus activity and connectivity. *Journal of Vision*, meeting abstract, 15:429.
- Qian, C. & Di, X. (2011). Phase or Amplitude? The Relationship between Ongoing and Evoked Neural Activity. *The Journal of Neuroscience*, 31(29):10425–10426.
- Raichle, M. E. & Snyder, A. Z. (2007). A default mode of brain function: A brief history of an evolving idea. *NeuroImage*, 37(4): 1083-1090.
- Raichle, M. E., & Mintun, M. A. (2006). Brain work and brain imaging. *Annual Review of Neuroscience* 29, 449-476.
- Ridley, M. (2003). *Nature via Nurture*, Harper Collins, New York.
- Romei, V., Brodbeck, V., Michel, C., Amedi, A., Pascual-Leone, A. & Thut, G. (2008). Spontaneous Fluctuations in Posterior  $\alpha$ -Band EEG Activity Reflect Variability in Excitability of Human Visual Areas. *Cerebral Cortex*, 18:2010-2018.
- Sadaghiani, S. and Kleinschmidt, A. (2013). Functional interactions between intrinsic brain activity and behavior. *NeuroImage*, 80:379-386.
- Schilbach, L., Eickhoff, S. B., Rotarska-Jagiela, A., Fink, G. R., & Vogeley, K. (2008). Minds at rest? Social cognition as the default mode of cognizing and its putative relationship to the “default system” of the brain. *Consciousness and cognition*, 17(2): 457-467.
- Schneider, S. L. and Rose, M. (2016). Intention to encode boosts memory-related pre-stimulus EEG beta power. *Neuroimage*, 125(15): 978-987.
- Scholvincka, M.L., Maiera, A., Yec, F.Q., Duynd, J.H., and Leopold, D.A. (2010). Neural basis of global resting-state fMRI activity. *Proceedings of the National Academy of Sciences of the United States of America*, 107(22): 10238–10243.
- Senior C., Lee N., & Butler M.J.R. (2011). Organizational Cognitive Neuroscience. *Organization Science*. 22(3). 804-815.
- Senior, C. and Lee, N. (2013). The state of the art in organisational cognitive neuroscience: The therapeutic gap and possible implications for clinical practice. *Frontiers in Human Neuroscience*, 7(808): doi: 10.3389/fnhum.2013.00808.
- Senior, C., Barnes, J., Giampietro, V., Brammer, M.J., Bullmore, E.T., Simmons, A., and David, A.S. (2000). The functional neuroanatomy of implicit motion perception or ‘representational momentum’. *Current Biology*, 10(1): 16-22.

- Sherrington, C. S. (1906). *The integrative action of the nervous system*. Yale University Press: New Haven.
- Sporns, O. (2011). *Networks in the brain*. The MIT press, Cambridge , USA.
- Stam, C.J. (2005). Nonlinear dynamical analysis of EEG and MEG: Review of an emerging field. *Clinical Neurophysiology*, 116:2266–2301.
- Sterman, M. B. (2000). Basic concepts and clinical findings in the treatment of seizure disorders with EEG operant conditioning. *Clinical Electroencephalography*, 31(1): 45–55.
- Tallon-Baudry, C. (2009). The roles of gamma-band oscillatory synchrony in human visual cognition. *Frontiers in Bioscience*, 14: 321-332.
- Tél, T. & Gruiz, M. (2006). *Chaotic Dynamics – An introduction based on classical dynamics*. Cambridge University Press, Cambridge, UK.
- Uddin, L.Q. and Menon, V. (2010). Introduction to special topic–resting-state brain activity: implications for systems neuroscience. *Frontiers in Systems Neuroscience*. 4(37): doi: 10.3389/fnsys.2010.00037.
- van Erp, J.B.F., Philippi, T.G., de Winkel, K.N. & Werkhoven, P. (2014). Pre- and post-stimulus EEG patterns associated with the touch-induced illusory flash. *Neuroscience Letters*, 562:79–84.
- Vecchio, F., Lacidogna, G., Miraglia, F., Bramanti, P., Ferreri, F. & Rossini, P.M. (14). Prestimulus Interhemispheric Coupling of Brain Rhythms Predicts Cognitive–Motor Performance in Healthy Humans. *Journal of Cognitive Neuroscience*, 26(9):1883–1890.
- Vernon, D. J. (2005). Can neurofeedback training enhance performance? An evaluation of the evidence with implications for future research. *Applied Psychophysiology and Biofeedback*, 30(4): 347-364.
- Vernon, D.J, Egner, T., Cooper, N., Compton, T., Neilands, C., Sheri, A., and Gruzelier, J. (2003). The effect of training distinct neurofeedback protocols on aspects of cognitive performance. *International Journal of Psychophysiology*, 47(1): 75-85.
- Waldman, D.A., Balthazard. P.A., and Peterson, S.J. (2011) Leadership and neuroscience : can we revolutionize the way that inspirational leaders are identified and developed? *Academy of Management Perspectives*, 25(1):60-74.
- Wang, G.Z., Belgard, T.G., Mao, D., Chen, L., Berto, S., Preuss, T.M., Lu, H., Geschwind, D.H. & Konopka, 8. (2015). Correspondence between Resting-State Activity and Brain Gene Expression. *Neuron*, 88(4):659-66.
- Wilson, E. (1998), Consilience - The Unity of Knowledge. *Vintage Publishers*, New York.

Zotey, V., Phillips, R., Yuan, H., Misaki, M., and Bodurka, J. (2014). Self-regulation of human brain activity using simultaneous real-time fMRI and EEG neurofeedback. *Neuroimage*, 85(3): 985-995.

## Figure caption

Figure 1 State space. Upper row: The pendulum as a dynamical system (see text for details). The panel on the right shows the circular attractors for the pendulum (solid: actual; dotted circle: reconstructed assuming a noisy measurement; dotted ellipsoid: noisy measurement reconstructed using sub-optimal embedding parameters). Even with noisy data, the reconstructed attractor is topological equivalent to a circle allowing faithful feature extraction. Lower row: Time evolution of the Henon system (x-axis shown, left inset), which is a 2-dimensional simplification of the Lorenz model of atmospheric convection. The time evolution is chaotic implying a complex attractor (left panel). The sensitive dependence on initial conditions is illustrated by the two dots that differed (in the past) by 1 part per million. The right panel shows the distribution of pre-stimulus brain states observed in a cohort of subjects performing a simulated shopping trip (measure STG; based on Braeutigam 2007). The states (columns) follow closely a statistical gamma-distribution (curve;  $\sim s^a e^{-bs}$ ;  $a \sim 1.4$ ,  $b \sim 0.003$ ) similar to that seen in models of duration of perceptual dominance evoked by bi-stable stimuli. Here, by analogy, individuals may fluctuate between certain states of the brain in order to balance anticipation of or preparation for upcoming shopping choices. The three snapshots (inset) illustrate apparently erratic pre-stimulus brain activity in one subject, which nevertheless contains a deterministic content excavated by non-linear state-space analysis. Note the topographical plots follow sequentially with a 0.005s time lag (left to right; sensor array projected into the plane, right ear at right, front at top)

FIGURE 1: STATE SPACE

