

NEURO-ENTREPRENEURSHIP

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Advances in the affordability and sophistication of neuroscientific techniques are allowing for the investigation of neural processes in domains such as marketing and economics, where neuroscience data is offering novel and often non-incremental contributions. In this study, we explore neuroscience and its' potential in furthering the study of entrepreneurship. We put forward an overview of neuroscience, discussing its key tenets, evolving boundaries and select methodologies. We outline a set of research areas in the domain of entrepreneurship that can be advanced via neuroscience—focusing on automaticity, individual differences, construct clarification and entrepreneurial learning. We also note several key challenges of applying neuroscience to entrepreneurship. The net effect of this cross-disciplinary effort is progress toward the establishment of a new discipline: neuro-entrepreneurship.

Keywords: Entrepreneurship; Neuroscience; Neuro-Entrepreneurship; Cognition

INTRODUCTION

Neuroscience research is rapidly advancing our understanding of the human brain (e.g., Adolphs, 2003; Bear et al., 2007; Deary et al., 2010). Tools that are becoming increasingly accessible and sophisticated, such as fMRI scanners and EEG headsets, allow for direct assessment of brain activity in unprecedented ways. As a result, multiple advances have been made that shed light on both the function and structure of the brain. These, in turn, provide new understandings of mental processes and their relations to behavior (see Lieberman, 2007 and Yarkoni, 2010 for extensive reviews). Researchers from a growing number of business disciplines are starting to leverage neuroscientific techniques to capture fundamentally new insights about their areas of inquiry. For instance, in marketing, Venkatraman et al. (2015) show that neural data is better at predicting advertising success as compared to traditional measures such as self-report purchase intents; in leadership, Waldman et al. (2016) advance a neural index that underpins ethical leadership; in finance, Bruguier et al. (2010) use neural data to advance our understanding of trader intuition.

Within the vibrant scholarly domain of neuroscience, inroads into entrepreneurship remain limited (De Holan, 2014; Krueger and Welp, 2014; McMullen et al., 2014; Nicolaou and Shane, 2014). This is rather surprising because, given that the field has much to gain from taking

research in this direction. Most entrepreneurship research relies on data from subject's recall, responses to developed scales, surveys, and secondary data analysis where underlying mental processes are not directly observed. In essence, the mental processes in the entrepreneurial setting are generally treated as a 'black box'. We argue that incorporating a neuroscientific approach can bring into focus a new level of knowledge, generating more nuanced insights that pertain to the mental processes which are central to many aspects of entrepreneurship. The potential of neuroscience within entrepreneurship, then, appears significant and may "change the way we see the entrepreneur, the entrepreneurial process and entrepreneurial management in general" (De Holan, 2014, p. 95).

This paper examines the potential of employing neuroscience in facilitating a better understanding of the mental processes of individuals engaged in the entrepreneurial setting. We first explore the promise of this research avenue by delineating its potential significance. Doing so, we put forward an overview of neuroscience and several key methodologies. Second, we delineate a set of research topics and research questions that can be augmented with neuroscience techniques and add greater understanding and insights to what we already know about entrepreneurship — placing focus on automaticity, individual-level differences, construct clarity, and entrepreneurial learning. Third, we present

several salient challenges of neuroscience research as applied to entrepreneurship. We conclude by discussing the implications of neuro- entrepreneurship for the existing domain of entrepreneurship research.

Adding to the nascent biological perspective of entrepreneurship (cf. Bönte et al., 2015; Nicolaou and Shane, 2009; Nicolaou et al., 2017; Shane and Nicolaou, 2015; Unger et al., 2015), this paper offers an in-depth overview of neuroscience and how it might go forward in entrepreneurship research. Viewed broadly, much as conceptual pieces have drawn attention to and kickstarted research across other sub-disciplines of neuroscience, such as neuro-strategy (Powell, 2011), our efforts lay a foundation for neuroscience-entrepreneurship research and call attention to its potential for advancing entrepreneurship scholarship. Collectively, the result is headway toward the establishment of a new sub-field—neuro-entrepreneurship—from which future researchers can develop.

THE PROMISE OF NEURO- ENTREPRENEURSHIP

Entrepreneurial Thinking

Decisions made in the entrepreneurial context have a significant impact on the individuals involved, the organizations they create and those whom the organization touches. Given the magnitude and importance of such decisions, researchers have long probed how individuals conceive of and develop new concepts (Choi & Shepherd, 2004), how they connect previously unconnected dots (Baron, 2006), and the reasoning that is used to arrive at decisions (Busenitz & Barney, 1997). Likewise, there has also been significant interest in entrepreneurs and how they may differ in their desire for achievement, the way they view risk, their need for control, and lack of conformity, among others. Furthermore, interest in entrepreneurial decision-making extends to investors that include business angels, venture capitalists and crowdfunders (Guler, 2007; Hildebrand et al., 2017; Huang and Pearce, 2015; Mitchell et al., 2002; Zacharakis and Meyer, 1998). Additionally, the first two decades of the 21st century have seen the emergence of entrepreneurial opportunities and understanding how and why they are recognized and exploited (Eckhart & Shane, 2003; Shane, 2000). Across all of these tangential areas, a common theme is an increasing implicit and often explicit focus on better understanding how individuals within the entrepreneurial setting “think”, and process information.

Investigating mental processes in the entrepreneurial setting, scholars have utilized a variety of approaches

such as self-report data (MacMillan et al., 1987), surveys (Murnieks et al., 2011; Gregoire and Shepherd, 2012) secondary data analyses (Allison et al., 2013), and qualitative techniques (Hindle, 2004). Aside from a few studies leveraging biology and behavioral genetics (Bönte et al., 2015; Nicolaou & Shane, 2009; Nicolaou et al., 2009; Shane & Nicolaou, 2015), present understandings tend to flow from approaches where inferences are drawn from attributes of observable actions and retrospective recollection. Yet, these techniques are subject to fundamental constraints because little can be directly observed on how the underlying decision and cognitive processes unfold. Thus, while inquiry of entrepreneurial thinking has emerged as an important area of entrepreneurship research, its progress is not without limitations. In light of the historical reliance on indirect observational data gives rise to the potential of exploring how neuroscience can augment our understanding of the mental processes that unfold within the entrepreneurial setting.

We believe that neuroscience can provide researchers important tools to enhance our understanding of entrepreneurship. Neuroscience can offer a novel and promising approach from which to improve our knowledge on how mental processes of entrepreneurial actors are carried out in the brain — processes that are otherwise difficult or impossible to detect through more traditional research methods. As Camerer et al. (2005, p. 10) notes: the “study of the brain and nervous system is beginning to allow direct measurement of thoughts and feelings. These measurements are, in turn, challenging our understanding of the relationship between mind and action, leading to new theoretical constructs and calling old ones into question.” Thus, the increasing availability and sophistication of neuroscience analytical approaches and methods offer a largely untapped line from which to launch inquiry — the brain — thereby complementing and potentially extending the ways entrepreneurial cognition is traditionally studied and understood (Krueger and Welp, 2014; McMullen et al., 2014). Because neuroscience in entrepreneurship “has been lacking and holds the potential to address important unanswered questions in the field” (Nicolaou & Shane, 2013), we seek to chart a path forward for this stream of research. We argue that the adoption of neuroscience offers the unique opportunity for providing the field a new apparatus with which to better understand entrepreneurial thinking. We suspect that our present understandings and assumptions will likely be challenged and open doors for new frontiers, which will be explored by our capacity to advance our comprehension of entrepreneurial mental processes as they unfold.

Advancing a neuroscience perspective requires a foundational understanding of what neural data can offer to entrepreneurial research. A central challenge of any cross-disciplinary work, and certainly with neuroscience, is that it necessitates knowledge foundations in both domains. In seeking to accelerate the learning curve for entrepreneurship researchers, we now offer a synopsis of neuroscience and the emergence of some key methodologies.

NEUROSCIENCE FOR ENTREPRENEURSHIP

In past few decades, neuroscience research has considerably advanced the study of the human nervous system and behavior. In particular, the emergence of brain imaging techniques, most notably EEG and fMRI, has opened novel opportunities to better understand the neural basis of people's decisions and mental processes (e.g., Dolan, 2002; Klimesch, 1999; Sanfey et al. 2003). Here, the study of the brain has resulted in an improved understanding of key brain regions, and knowledge about how activations in certain regions underpin individual thought and behavior. The study of automaticity, for instance, sheds light on the quick and intuitive neural region activations that augment current understandings about individual thinking and behaviors (Jeon & Friederici, 2013; Winston et al., 2002). Thus, through observing neural activity while engaging in carefully designed tasks, researchers continue to make impressive advancements through the direct observation of brain activations. Specifically, in the last two decades, neuroscientists have mapped key neural sites that are implicated with processing that is essential for the understanding of the underlying mechanisms of decision-making (e.g., the anterior cingulate and orbitofrontal cortices and their interplay with the supplementary and pre-supplementary motor areas to generate an action), emotion (e.g., from the regulation of the emotion by orbitofrontal cortex to the manifestation of ones in areas such as the amygdala), reward and learning (e.g., the nucleus accumbens and the ventral-tegmental areas), memory (e.g., interplay between frontal regions and the gateways to memory processing such as the hippocampus), attention (e.g., numerous sites ranging from the inferior-temporal areas and the inputs from various senses that lead to the binding of a coherent experience), and more.

Given this progression, the increased interest in the human brain within business disciplines is unsurprising. This attention has resulted in calls and efforts to better understand the neuro-cognitive foundations of strategic processes (Powell, 2011), organizational behaviors (Becker & Cropanzano, 2010), leadership (Waldman et al., 2011), finance (Bruguier et al. (2010), among others.

Moving to consider the application of neuroscience to entrepreneurship, a logical starting point is introducing and establishing working knowledge of the key neuroscience methods that are optimally suited for the study of entrepreneurial thinking. Here, we specifically focus on two methods that, due to their characteristics and potential, offer viable paths for investigating entrepreneurial cognition: electroencephalography (EEG) and functional Magnetic Resonance Imaging (fMRI).

Electroencephalography (EEG)

Overview. Electroencephalography (EEG) is a non-invasive technique which records electrical signals of the brain by using electrodes positioned on a subject's scalp. EEG has been utilized in neural research for decades. Undergoing steady technological advancements, EEG remains a ubiquitous method given its many advantages. The physiological basis of the EEG signal originates in the currents of specialized projections of cortical neurons (i.e., postsynaptic dendrites) (Nunez, 1981). Indeed, neurons are the "atoms of cognition" (Fried et al., 2014) and are excitable cells that allow information flow through electrical and chemical signals. EEG measures voltage fluctuations resulting from ionic current within the neurons of the brain. By measuring the residual fluctuations of those current researchers can have subjects engage in a wide range of tasks while observing the electrical activity that stems from brain regions of interest.

For signals to produce an electrical field large enough to be detectable at the scalp, a group of neurons, aligned in parallel, must be active in synchrony. While necessary, this orientation requirement also represents an intrinsic constraint of the technique, because it allows recording only from brain areas in which neurons are arranged in this way. Simply put, this indicates that with EEG it is difficult to directly assess brain structures located below the outer (cortical) layer. Nonetheless, EEG is well suited to record cortical activity, and it has excellent temporal resolution: recording activity at frequencies as high as 1000Hz, which is the timescale by which neurons activity is exhibited (typical neurons burst are at the order of milliseconds). Indeed, because changes in the electrical signals associated with cognitive process are conducted instantaneously at the scalp, EEG is exceptionally suited to appreciate the timing of a cognitive event (Sutton et al. 1965).

In order to record such variations, a standard EEG apparatus uses a multichannel amplifier connected to several conductive electrodes (with a typical research setting holding between 32 up to 128; or more in high-

density devices) placed on the subject's head and usually inserted in a wearable head cap. It often takes time to prepare the EEG, because it requires the precise placement of the electrodes and the use of conductive gels or solutions (typical setting of 32- electrode EEG system ranges between 10-20m for experienced researcher. Larger number of electrodes clearly require more time but lead to higher accuracy in the reading). The electrodes must be arranged at various locations on the scalp, which are usually described with reference to the "International 10–20 System" (Klem et al., 1999 for a review). The electrodes are labeled with a letter, indicating their anatomical location (C = central; F = frontal; O = occipital; P = parietal; T = temporal), and a number indicating the hemisphere (odd numbers are used for recordings from the left hemisphere; even numbers for the right hemisphere; "z" labels the midline). The acquired signals are then digitized into a computer, processed, and analyzed.

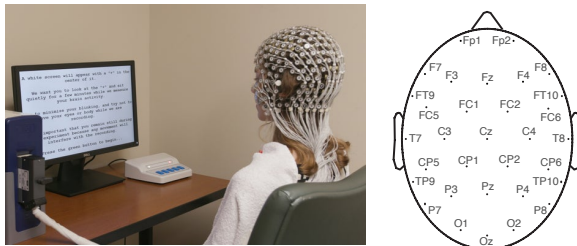


Figure 1. Left: EEG in use. **Right:** Typical "montage" of electrodes placed on a subject's head – from above.

Frequency Analyses. EEG records spikes and waves in the electrical activity of the brain, which oscillate at different rates or frequencies. Standard frequency waves that are correlated with specific behaviors are named. These include alpha waves, with oscillations in the 7 to 13 Hz range; beta waves, in the 13 to 20 Hz range; and, gamma waves in the 20 Hz and above range. Delta and theta waves are in the 1-4 Hz and 1-8 Hz ranges, respectively. Other wave bands exist and reflect more nuanced frequencies that are relevant for specific research areas.

While these frequencies naturally occur, several efforts have been made to link patterns of oscillations to distinctive cognitive functions (Başar et al., 2001). For example, alpha waves at the back of one's brain (electrodes O1 and O2) are often implicated with increased visual attention in a task. Yet, due to low specificity and the traditional reliance on visual analyses of the waveforms, early attempts of mapping a frequency band with a particular cognitive process were also often imprecise (as reported in Harmon-Jones and Peterson, 2009). More recently, however, the increasing use of spectral power analyses has offered more robust

approaches (e.g., Fitzgibbon et al., 2004). For example, research in personality has examined differences in the frontal cortical activity, in particular in relation to emotional processes. Research has shown that greater relative left and right frontal EEG activities, measured as alpha power asymmetry, relate to individual differences in positive and negative affect respectively known as "approach-avoidance measures" (Tomarken et al., 1992). This evidence has in turn offered a neurophysiological basis to the so called "affective valence hypothesis" (Harmon-Jones and Allen, 1998).

Event-Related Potentials (ERPs). A common index of brain activity related to EEG signals are ERPs. ERPs refer to averaged EEG responses that are the direct result of a specific cognitive event or stimulus (Teplan, 2002). When EEG is recorded during an experimental task involving specific events, it is possible to examine those EEG periods (epochs) that expose neural processes distinctively associated to those occurrences. Thus, while wearing an EEG cap, respondents engage in a series of repeated manipulated conditions, or trials, where the neural responses to such conditions are then averaged. ERPs is a reliable method to study the physiological correlates of cognitive activity associated with processing information (Handy, 2005), however it requires significant number of repeated trials to be able to average the signal from noisy fluctuations that often occur spontaneously.

The signals are represented graphically by plotting time (in milliseconds) on the x-axis and electrode potential (in microvolts; the impedance level of typical EEG electrode) on the y-axis. The resultant chart consists of a series of positive and negative peaks for each electrode, each with a slightly different outline. The peaks are labeled with "P" (positive) or "N" (negative) and numbered. For instance, P1, P2, and P3 refer to the first, second, and third positive peaks, respectively. Alternatively, they can be marked with the timing of the peak (i.e., P300 refers to a positive peak at 300 milliseconds). It is worth noting that the polarity of a peak has little meaning in cognitive terms, nor does a positive peak reflect excitation, and a negative peak inhibition (if anything, in most EEG systems those are reversed, as the reading of the ionic discharge from the outside of the neurons is opposite in polarity to the actual discharge in the cell). These labels mostly depend on the spatial arrangement of neurons giving rise to the signal at that particular moment in time. However, the characteristic peaks and troughs of the ERP waveform can be linked to cognition by assessing timing, latency, and amplitude of the peaks (e.g., Polich and Kok, 1995). For example, showing subjects repeatedly images of faces vs. objects and then averaging the neural activity at the onset of a

face image will often yield a consistent increase in EEG reading at the 300-millisecond mark (P300) in temporal electrodes.

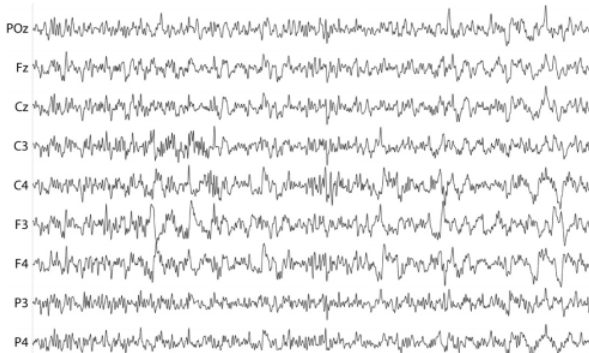


Figure 2. Sample EEG results.

The difference of the ERP signal are named components or deflections the most common being N1, P3, N100, P300, (Donchin, 1981). Traditionally, ERP components have been classified as either exogenous (or evoked potentials), which depend on the physical properties of the task such as size or intensity, or endogenous, which rely the subjects' intentions and can also occur in the absence of an external stimulus. Importantly, another way to classify ERP data is to consider the 'time-locked', 'response-locked' or 'anticipatory' waves (Amodio et al., 2014). These terms refer to the way the epochs of the EEG signals are combined during the averaging process. For instance, in the stimulus-locked waveform all the epochs are averaged to the time of the stimulus onset; in the response-locked waveform they are aligned to when the task response is made by the subject. Anticipatory responses occur prior to the stimulus onset.

ERP research has been widely exploited to inform the unobservables that underpin thinking and action. For instance, Cacioppo et al. (1993) have shown that the P3 amplitude is often augmented when a stimulus represents a category different from a precedent stimulus (i.e., the oddball paradigm). Because attitude characterizes evaluative categorizations, they showed that subjects' inconsistent attitudes elicit larger P3 than consistent attitudes. These results have thus offered evidence in support of studying personal attitudes with a methodology that does not rely on self-reported data, as formerly done (Ito and Cacioppo, 2007).

Strengths and Weaknesses of EEG. Notwithstanding some limitations — namely, the low spatial resolution (inability to differentiate specific regions), the challenges in detecting inner brain region activity, the poor signal-to-noise ratio and the lengthy set-up preparation time — EEG offers a number of benefits to cognitive research in

entrepreneurship. The costs are significantly lower than those of most other neuroimaging techniques, often a fraction of alternative approaches. Moreover, the method is silent, and does not generate any potentially distracting noise. In addition, it is more portable than other approaches, allowing for greater flexibility in the data collection setting. Notably, recent EEG technologies are wireless, allowing for the exploration of neural activities in unprecedented ways (e.g., group/team interactions, etc.). In terms of research design, ERP studies can be conducted with relatively simple paradigms. As discussed, EEG has excellent temporal resolution which makes it feasible to link to neural processes in the brain. ERPs also allow the measurement of electrophysiological variation associated to when the subject is not attending to the stimuli, thus informing interactive properties of stimuli and stages of processing (Serenio et al., 1998). Finally, unlike fMRI or other imaging methods that rely no signal that is not directly neural, the mechanisms by which the brain elicits the response measured by EEG are fully understood and one can tie an effect directly to a brain activity.

In recent years, other EEG-based approaches have emerged. In clinical and leadership research, for example, quantitative EEG (qEEG) has found increasing attention (Waldman et al., in press). Indeed, while EEG frequency analyses cannot provide direct information on anatomical origins of signals, qEEG offers topographic display and analysis of brain electrophysiological data by leveraging on Fourier analysis of the EEG signal. Likewise, technological advancements are offering opportunities of dry sensors. Dry sensors are ones that do not require additive gel to be placed between the scalp and the electrode for reduced noise, thus allowing both increased accessibility and reduction of preparation time.

Functional Magnetic Resonance Imaging (fMRI)

Overview. The brain can be visualized by using both structural and functional imaging. Magnetic resonance imaging (MRI) is one of the most commonly used structural imaging techniques that leverages nuclear magnetic resonance principles (Lauterbur, 1973; Mansfield and Grannell, 1973), allowing the visualization of different types of brain tissues — gray matter, white matter, and cerebrospinal fluid. Functional MRI (fMRI) measures brain activity by capturing changes associated with blood flow in the brain (Logothetis et al., 2001; Ogawa et al. 1990); differently from EEG, fMRI does not directly measure neurons' activity, but rather the residues of the blood flow in the brain as a proxy for neural activity. In fact, fMRI primarily relies on variations of the signal associated with the level of oxygenated blood in a given region of the

brain (BOLD or blood-oxygenated level dependent signal) (Ogawa et al. 1990). Indeed, it is important to appreciate that our brains, like any other part of our body, consume oxygen, carried in circulation by hemoglobin, and glucose at variable rates depending on the level of activity required. Thus, when a particular brain region is actively engaged in a task, blood flow increases (Mosso; see Zago et al., 2009) so that it can quickly use the nutrients available at that moment, also turning oxygenated hemoglobin into deoxygenated. The way in which BOLD signal evolves in response to an increase in neural activity is called the hemodynamic response function (HRF), which is characterized by distinct phases. The HRF is generally stable in the same participant in the same brain region. Yet, it varies between participants and across different brain regions (Aguirre et al., 1998). Thus, as subjects engage in tasks, dynamic maps of the moment-to-moment activity of the brain during a cognitive task can be modeled.

fMRI research is performed with a MR scanner, a very powerful, large and loud magnet, capable of generating magnetic field several thousand times stronger than the Earth's magnetic field. The magnet's strength is measured in Tesla (T) and a typical scanner for fMRI research has a field strength of 1.5T or 3T. During an fMRI measurement one subject lays inside the bore of the magnet, and the magnetic field is applied constantly across the brain, while the subject is either resting or performing a simple cognitive task. The signals are then analyzed through a series of complex passages and fMRI images are constructed according to voxels—3D pixels carrying volumetric information on the brain. Hence, the spatial resolution of fMRI depends on the size of the voxel, usually around 1mm^3 . Using fMRI, there is a delay in temporal resolution, where the blood flow to a certain brain region is lagged by a few seconds after the region has been activated. Notably, because magnetic fields can penetrate the skull, fMRI produces a reading of the whole brain, or a high-density image of a specific brain location – including structures buried deep inside our heads. Therefore, unlike EEG, fMRI is able to yield indicators of neural responses in sites that are deep beyond the cortex.



Figure 3. fMRI in use.

Blocked and Event-Related Designs. The consideration of which stimuli to employ in fMRI research is a paramount step of a study's research design. Due to the considerable noise in the BOLD signal, multiple repetitions of a condition are required to gain sufficient power and reliability. Two main categories exist: block and event-related designs (see for review Amaro and Barker 2006).

In the block design, multiple stimulus repetitions that belong to the same experimental condition are grouped together. Each block lasts around 20-40 seconds (given that a typical neural decay of the blood flow is in the order of seconds) and there is a minimum of 2 to 4 blocks per condition. Clearly, the more repetitions the more reliable the signal. With such designs, the collection of cognitive and behavioral measures is possible for statistical analyses across participants. In the event-related case, different stimuli or conditions can instead be scattered with each other and separated during data analysis. Importantly, the event-related design allows both across- and within-participant analyses (Josephs et al., 1997).

Block designs have an advantage over event-related designs because they have more power — i.e. they capture significant but small effects. Yet, a major limitation of blocked designs are situations in which it is challenging to know how stimuli behave relatively to each other, and therefore they cannot be grouped. In these cases, event-related designs enable a wider range of experimental designs and more adherence to the traditional format of psychological and behavioral experiments (Josephs & Henson, 1999). Mixed blocked- and event-related designs are also increasing popular avenues in functional neuroimaging research (Donaldson, 2004).

Experimental Strategies. There are several ways to design a task for an fMRI experiment. One of the most

common is that of cognitive subtraction, which compares the activity in different brain regions in response to a particular cognitive task (Friston et al., 1996). This design compares two brain states that are believed to differ in the independent variable only. The rationale relies on the assumption of “pure insertion”: A single cognitive process can be inserted into a task without affecting the remaining processes, and there are no interactions among the cognitive components of a task. For these reasons, the choice of a baseline is crucial in this type of experiments because it needs to be as similar to the experimental task as possible in order to accurately reveal the specific regions involved in the cognitive processing (Logothetis, 2008).

Another widely used method is that of cognitive conjunction, which allows the assessment of regions of activation that are shared across several different stages of a cognitive process (Price and Friston, 1997). Typical studies are designed so that two or more distinct tasks share a common processing difference. The neural correlates of the process of interest are then associated with the common areas of activation for each task pair. This approach does not depend on pure insertion and offers more flexibility in the choice of the baseline. While a baseline is still required, the problem of interactions between brain regions involved in multiple processes is reduced.

In a parametric design, the variable of interest is instead treated as a continuous dimension, which essentially means it has an infinite possible values. This approach measures associations between brain activity and changes in the variable of interest rather than differences in brain activity between conditions as in the other types of design. Parametric designs use correlations for data analysis and the effects of the experiment are usually evaluated globally across all levels of the factor.

Finally, the approach of functional integration models how different brain regions’ activities influence each other (Van Den Heuvel, 2010). This allows inferring the effective connectivity or functional connectivity between regions when performing a task. This approach relies on Principal Components Analysis (PCA; which transform possibly correlated variables orthogonally into linearly uncorrelated variables) to reveal the overall variance between groups. Recently, functional integration studies have been designed without a definite experimental task which are known as resting state paradigms: participants are asked to lay back and rest and the fluctuations in brain activity are measured (De Luca et al., 2006).

Given that many of those techniques begin with an hypothesized neural site that is suspected to be involved

with the task at hand, prior to any experimental design, researchers often engage the subject in a ‘masking’ task, or ‘ROI’ task. The masking task is one that was previously identified to elicit specific known activity in a certain area (i.e. emotional images which generate consistent predictable activity in the area known as the amygdala). This allows for the localization of the area in the subjects brain precisely, which is later used for alignment of the results to the specifics of the brain and the certainty in identification of the relevant areas for a task.

fMRI Data Analysis. As it happens with EEG analyses, also fMRI data requires complex pre- and post-processing steps performed with dedicated algorithms and procedures. The first step in pre-processing is usually the slice timing correction (Sladky et al., 2011). Because the MR scanner acquires different slices of the brain at different times, each slice shows brain activity at a different time, therefore a timing correction is applied to bring all slices to the same reference.

Another main passage is the correction for head movement: if a participant moves their head in the scanner also the position of any active region moves (Thesen et al., 2000). This can result in a given region being more difficult to detect, due to the activity being dispersed, or in a false- positive. Additionally, to dedicated algorithms, head movements can also be minimized by physically restraining the head in position, and instructing the participants to keep as still as possible.

Stereotactic normalization, which involves mapping regions on each individual brain onto a standard brain, is another important data processing stage (Thirion et al. 2006). Each brain is divided up into thousands to millions of voxels, each with spatial coordinates mapped onto the corresponding coordinates on any other brain. Mathematical transformations are applied to each brain image to fit it into a standard space, generally provided by the brain atlas of Talairach and Tournoux (1988).

Finally, smoothing enhances the signal-to-noise ratio and is an advantage for analyzing groups of subjects. Smoothing increases the spatial extent of active regions by “spreading” the activation signal to neighboring inactive voxels. It thus increases the chance of finding common regions of activity because the procedure involves averaging the activity across individuals. Yet, clearly, if a study focuses on individual differences, researchers would generally waive this step (Hagler et al., 2006).

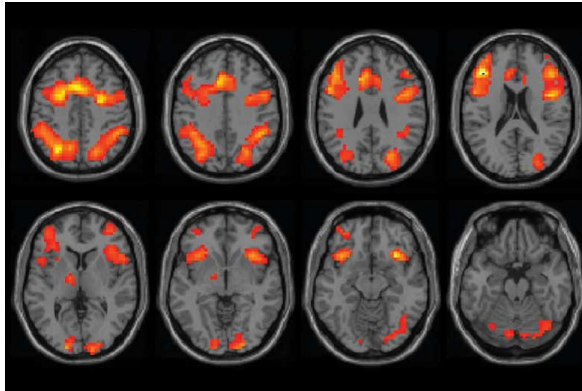


Figure 4. Sample fMRI data.

Strengths and Weaknesses. Several approaches are available for setting up experiments in functional Magnetic Resonance Imaging, which makes it a versatile technique applicable to different types of cognitive tasks in entrepreneurship research. It is therefore important to ensure that each strategy is fitting the research question and hypotheses being tested. It is also worth noting that there are several reasons why a brain region may be active, and not all of them may be always relevant to an experimental task. For instance, an increase in signal could reflect the strategy that the participants happen to adopt in the task, or some general mechanism not specific to the task, such as increased attention, or even represent unrelated physiological processes such as inhibition of neural activity. Moreover, there is a general assumption of linearity between the BOLD signal and the baseline activity, and the technique is not well-suited for investigation of long-term changes in neural activity, such as in neurofeedback protocols.

Aside from these limitations, which are anyway well known within the neuroimaging community and should not be a reason to detract this method, conducting fMRI research has more timely drawbacks. fMRI research is considerably expensive, with sessions typically ranging from \$500 to \$1000 per hour, or subject. Further, the physics of the technique do not allow it to be performed outside the MR suite, thus raising issues of ecological validity. Finally, the fact that fMRI results typically yield thousands to millions of voxels suggests that, at random, certain number of voxels are likely to correlate with a behavior. If the analysis does not correct for multiple comparisons then most fMRI studies will in fact find a brain region that miraculously seems to correlate with a behavior. This seemingly easy-to-fix statistical fluke is actually rampant in numerous fMRI studies and yielded a large controversy as to whether much of the results are in fact true. Meta-analysis of fMRI studies time and again reveal malpractices in the analysis that draw incorrect conclusions.

Nonetheless, fMRI has clear benefits over other neuroimaging methods if the researcher is interested in higher spatial reading at the expense of rapid temporal resolution. Spatial accuracy allows for fine-grained distinctions between sub-regions that specialize in a particular function. Ultimately, simultaneous recording with EEG and fMRI (i.e., co-registration) is an emerging approach in neurocognitive research that allows for complementing the strengths of both methods (Laufs et al., 2003).

APPLICATIONS TO ENTREPRENEURSHIP

We next focus on several areas of entrepreneurship research to illustrate how they may potentially be expanded via the integration of neuroscience. The application of these techniques holds potential to offer unique complementary data, create new insights beyond what currently exists, and to explore brain underpinnings associated with entrepreneurship theories. Illustrating how neuroscience may advance research in entrepreneurship, we specifically focus on discussing automaticity, individual-level differences, construct clarity, and entrepreneurial learning as potential research directions, respectively. We also note several challenges of neuro- entrepreneurship research in Table 1 below.

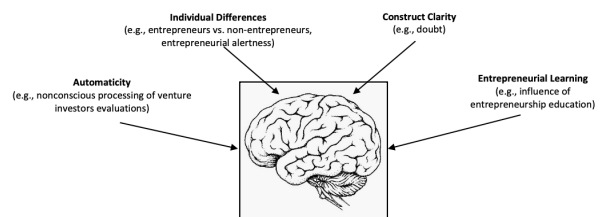


Figure 5. Key research directions in Neuro-Entrepreneurship.

Challenges	Description	Proposed Solution
Cross-Disciplinary Teams	Divergent reward structures	<ul style="list-style-type: none"> Collaborating with business school-based neuroscientists (as with this project) Multiple projects from data collection efforts targeting multiple, yet different, research domains suitable to both neuroscience and business journals
Knowledge Foundations & Culture	Knowledge foundations fundamentally differ. The culture of the fields of business vs.	<ul style="list-style-type: none"> Committing to time investment that leads to a thorough understanding of respective disciplines

	neuroscience leads to numerous clashes on the research style.	<ul style="list-style-type: none"> • Flexibility in adapting to differing cultural norms • Generate journals that are dedicated to the field
Cost	The collection of attaining neural data can be prohibitively expensive	<ul style="list-style-type: none"> • Cost sharing with coauthors and neuroscience labs • External (grant) funding -Judicious Pilot Testing
External Validity	Data collections in unnatural settings	<ul style="list-style-type: none"> • Appropriate research questions and experimental design • Triangulation

Table 1. Challenges of Neuro-Entrepreneurship research and proposed solutions.

Can neuroscience inform automaticity in entrepreneurship?

A key strength of neuroscience is the capacity to observe the previously unobservable in the brain. The ability to capture automaticity, or the automatic and often non-conscious processing that occurs stands as a hallmark example. Automatic processes have long been argued to be a longstanding component of judgment and decision making research (e.g., Chaiken and Eagly, 1989; Tversky and Kahneman, 1975), where neuroscientists continue adding evidence that supports this notion, regularly highlighting that at least 90% of all brain activity never reaches consciousness. Neuroscience data in particular, sheds light on automatic brain activations that underpin judgments, decisions and behaviors (Bryant et al., 2008; Öhman, 2002; Tamietto and De Gelder, 2010; Tusche et al., 2010; Venkatraman et al., 2012, 2015). Here, it is suggested that nonconscious processes serve as a cornerstone that guides behaviors prior to consciousness (Bechara et al., 1997). As such, much can be learned from direct observation of mental processes. The domain of neuro-marketing or consumer neuroscience, for example, largely focuses on capturing neural mechanisms linked to consumer purchase intentions — particularly those occurring beyond the evaluator’s conscious recognition (Ariely and Berns, 2010; Meckl- Sloan, 2015; Venkatraman et al., 2015). A growing number of studies illuminate such links, where, for instance, distributed activation across the anterior insula and medial prefrontal cortex during preference ratings of cars reliably predict purchase preferences before decisions were made — even prior to respondents’ awareness of their task to reveal their purchase preference (Tusche et al., 2010).

Similarly, neural data can provide important, previously unobservable clues into the workings of the mind — particularly outside of conscious awareness.

Shifting to the area of entrepreneurship, there are many areas of inquiry where the observation of automatic responses could further inform important evaluations and decision processes. For example, significant research attention has been devoted to understanding how and why external stakeholders, such as venture capitalists (VC), angel investors, and Initial Public Offering (IPO) investors, make decisions about funding young, entrepreneurial firms (e.g., Huang and Pearce, 2015; Martens et al., 2007; Zacharakis and Meyer, 1998). While considerable work has established characteristics of the opportunities and the cognitive processes influencing such evaluations, we presently lack evidence on the automatic processes that influence these unique decisions. Here, extant research from the fields of psychology and neuroscience make clear that decisions are influenced by, and largely predicated on fast, non-conscious processes — yet such processes stand largely unaccounted for across the entrepreneurial setting. Guy Kawasaki, a prominent VC, hints at the potential salience of such processes by noting: “In the first five, ten, or maybe fifteen seconds [investors] decide...And that has important consequences.”

Neuroscience techniques hold the potential to offer a first look into the key influences or automatic neural processes that shape decision making — stages much earlier than what most investors can consciously or retroactively articulate with accuracy. Such approaches could allow us to begin tapping into the key neural processes that underpin how investors assess investment prospects in this unique decision context, such as viewing the entrepreneur’s pitch. Early activation in the ventral striatum, for example, may be particularly relevant given its link to the reward system — and in particular motivations for ‘wanting’ versus simply ‘liking’ an object (Knutson et al., 2007). Are there early neural predictors, such as the ventral striatum, that, if triggered, set decision makers on a path to more or less favorably evaluate an opportunity? Are there activations that *must* occur within a certain time frame for a favorable evaluation? How do the relevance and predictive utility of various automatic processes differ when evaluating different types of entrepreneurial investment opportunities, such as financial- or social-focused opportunities? What role do neural responses shown to automatically imitate those of another (e.g., a pitching entrepreneur or other investors) play in shaping investor evaluations? Along the same lines as neuro-marketing, if we can first understand the relevant neural substrates at play with favorable (or unfavorable) entrepreneurial

investment evaluations — particularly those that are otherwise hidden — we can draw on extant neuroscience research to reverse engineer the entrepreneur’s pitch, emphasis, and/or approach to increase the odds of tapping into (or avoiding) critical neural activations. In exploring the neural activity of investors, controlled experiments could be deployed as investors evaluate a series of carefully manipulated entrepreneur pitch videos or abbreviated business plans while undergoing brain imaging.

In sum, adding neuroscientific data could begin shedding light on key processes that occur outside of conscious awareness. Doing so could help to refine theory and current understandings about the nature of automaticity in the entrepreneurial setting — venture investors and beyond.

Can neuroscience inform individual differences in entrepreneurship?

Neuroscience research has long explored how differences across individuals can be observed through neural processes (DeYoung and Gray, 2009; Eddington et al., 2007; McRae et al., 2008) — e.g., “Neuroimaging...has begun to identify how variability in brain function contributes to individual differences in complex behavioral traits” (Hariri, 2009). Because neuroscientific approaches have been useful in the development and advancement of theory explaining various elements of such differences, they are poised to prove useful in the study of entrepreneurship.

Key differences of individuals in the entrepreneurial setting should be traceable to the origin of where these differences manifest (i.e., the brain), thereby offering an avenue to enrich our current understanding of their nature and distinctiveness (McMullen et al., 2014).

Seeking to understand how individual-level differences emerge in the realm of entrepreneurship has been the focus of significant research attention. Consider that efforts have been made to understand differences across individuals, particularly in their experience and willingness to engage in key entrepreneurial activities. Here, scholars have explored variation in entrepreneurial experience (e.g., entrepreneurs vs. non-entrepreneurs), as well as variation in individual levels of entrepreneurial alertness (cf. Baron and Ensley, 2006; Busenitz and Barney, 1997; Kirzner, 1999; McGrath et al., 1992; Stewart et al., 2001; Tang et al., 2012). Seeking a neuroscientific plausible explanation of such differences in entrepreneurship stands as a potentially profitable path to better understand the nature of such variance (McMullen et al., 2014). In this way, we could observe

how neural processes vary as a function of being high and low on individual-level scales or thresholds, advancing an early foundation of a neuroscientific basis/theory of oft-studied individual differences in the entrepreneurship literature.

Splitting samples by the median and observing neural activity of subjects as they evaluate a series of actual or manipulated entrepreneurial opportunities (Gregoire and Shepherd, 2012; Haynie et al., 2009), or while completing relevant tasks used in past neuroscience studies, such as creativity tasks (Dietrich, 2010; Fink et al., 2014; Shah et al., 2013), ambiguity tasks (Camerer, 2007; Neta et al., 2013), or risk and reward tasks (Peterson, 2005; Rao et al., 2008) represents a viable path. For example, do neural differences emerge when comparing novice entrepreneurs to serial entrepreneurs, or entrepreneurs to non-entrepreneurs? It is conceivable to theorize that, given the role of optimism in entrepreneurship (Hmieleski & Baron, 2009), those with higher versus lower entrepreneurial experience, or entrepreneurs versus non-entrepreneurs, reflect greater activation in the rostral anterior cingulate cortex given the documented relation to optimism (Blair et al., 2013; Sharot et al., 2007). Do variations in entrepreneurial experience impact neural processes associated with intuitive decision making, such as differential use of the X-system and C-systems (Lieberman et al., 2004)? Do those with greater entrepreneurial experience reflect neural differences across key regions, such as the cingulo-opercular network (dorsal ACC [dACC]/medial superior frontal cortex and the bilateral frontal operculum [FO]/anterior insula), given their relation to tolerating and managing ambiguity? Experiencing adversity influences brain functioning in numerous ways (Boecker et al., 2014) — do neural responses to adversity vary as a function of those higher versus lower in entrepreneurial experience? Moreover, do those higher in alertness reflect greater activation in the left inferior parietal cortex due to its link to creativity and the generation of new ideas (Fink et al., 2014)? By extension, if we are able to uncover neural bases that are common to high and low segments of such individual differences, then exploring exercises and interventions that increasingly lead one to utilize such neural functioning may be plausible. In this way, the uncovering of key neural patterns may shed new light on the relative malleability of individual differences from a neuroscientific standpoint. Can neuroscience aid in informing whether and precisely how individuals can increasingly tap into the requisite neural functioning that results in a higher likelihood of entrepreneurial action?

In sum, identifying a neural basis of individual differences in entrepreneurship, and the neural impact of

potential interventions holds the potential to generate rich insights going forward.

Can Neuroscience inform key constructs in entrepreneurship?

An advantage of neuroscience techniques is the ability to localize and differentiate constructs of interest. In this vein, neuroscientists regularly use brain imaging to map certain constructs to their underlying neural substrates. Doing so offers a fresh look into the neural activities associated with commonly studied constructs, and can shed light on their dimensionality and underlying mechanisms. Neuroscientists, for instance, have shown that brain regions associated with potential losses (loss aversion) or gains appear as distinct dimensions (Kuhnen & Knutson, 2005; Reimann et al., 2011; Tom et al., 2007; Trepel et al., 2005). Such insights offer clarification about why prospective losses are weighted more heavily than gains and that their activations are not mutually exclusive — having a number of implications for prospect theory. Moreover, based on fMRI scans, Dimoka (2010) has shown different neural correlates for trust and distrust, revealing how they represent distinct constructs. Here, trust activates brain regions, such as the caudate nucleus that is associated with positive reward anticipation, while distrust is linked to areas of intense negative emotions and fear, such as the amygdala, and insular cortex. These findings add to the debate on trust and distrust — namely that they do not reside on the same continuum, can co-exist, and that trust is more cognitive and calculated and deliberated while distrust is more emotional. Moreover, exploring distinctiveness across constructs via fMRI, Daw et al. (2006) advance ambidexterity in decision making, uncovering that exploration and exploitation, a fundamental paradigm for entrepreneurial cognition, have distinct neural correlates. In particular, frontopolar cortex and intraparietal sulcus are preferentially active during exploratory decisions, while regions of striatum and ventromedial prefrontal cortex exhibit activity characteristic of an involvement in value-based exploitative decision making. Collectively, it is clear that brain imaging technologies can offer unique evidence on the inherent nature of constructs of interest.

Neuroscience tools may prove helpful in the localization and differentiation of commonly employed constructs in entrepreneurship. For example, scholars have investigated constructs such as doubt (McMullen and Shepherd, 2006; Shepherd et al., 2007) as a critical antecedent to entrepreneurial action. Do varying levels, such as high or low levels of experienced doubt around an entrepreneurial opportunity reside on a continuum, or might high and low of each be tied to fundamentally

different neural functions — akin to trust and distrust? Understanding which neural regions are associated with high levels of doubt could help to better understand its underpinnings — perhaps providing new insights on its origination and role during controlled opportunity assessments. Importantly, mapping the neural correlates of key constructs in entrepreneurship also offers the potential to decipher the relation (or lack thereof) among multiple constructs of interest; put differently, exploring commonalities and distinctions *across* competing or tangential constructs is viable. Inquiries into the neural basis of constructs in the entrepreneurial setting can help uncover new differences and potential overlap. With regard to neural functioning, how does doubt differ from other important antecedents to entrepreneurial action, such as optimism? Is there significant overlap or clear points of distinction? Do neural functions associated with high levels of one impede the other, or are they distinct enough that their inverses can function simultaneously when assessing an opportunity?

In sum, the localization and differentiation of constructs via neural data stands as a path to advance and clarify constructs that are often studied in the realm of entrepreneurship.

Can neuroscience inform entrepreneurship education?

While educational initiatives and learning, in general, are often examined through observational studies, longitudinal neuroscience studies offer a path to observe the resultant influences and changes on the brain (e.g., Bangert and Altenmuller, 2003; Dahlin et al., 2008; Stewart et al., 2003). Doing so can help to determine whether and how brain functioning changes as a result of training or learning. Neuroscience longitudinal research, for example, reveals shifting brain activation following certain training tasks (e.g., from parietal and occipital areas to temporal regions) (Poldrack et al., 1998; Kassubek et al., 2001; Thomas et al., 2009). Ilg et al. (2008) find changes in grey matter over time via practicing certain complex procedural learning tasks. Goswami (2006) notes that “...our understanding of the neural bases of the '3 Rs' — reading, writing and arithmetic — is growing rapidly. So is our understanding of how to optimize the brain's ability to benefit from teaching.” Thus, tools of neuroscience are beginning to offer a unique view into the brain's response (or lack thereof) to education and learning.

Given the surge of interest in entrepreneurship education activity (Kuratko, 2005; Vesper and Gartner, 1997; Bae et al., 2014; Henry et al., 2005; Martin et al., 2013; Rauch and Hulsink, 2015; Siegel and Phan, 2005), tools of

neuroscience may aid in better understanding the resultant impact. Here, entrepreneurship education efforts tend to operate under the assumption that entrepreneurship can be taught, where such initiatives ultimately result in cultivating entrepreneurs over time. But entrepreneurship education remains controversial: “very little evidence exists” on the impact of entrepreneurship education (Kauffman Foundation, 2016), and “While many entrepreneurial education and training courses are being offered to entrepreneurs and future entrepreneurs, we don’t know a lot about what is working” (Kauffman Foundation, 2015). The mixed findings have resulted in calls for more research and greater methodical rigor to better understand the impact of entrepreneurship education (Rideout and Gray, 2013). Thus, a complementary window into the influence of entrepreneurship education could be observed through a neuroscience approach. Comparison of neural data against control groups before and after different variants of entrepreneurship education take place could cast new light on the effect of such efforts, helping to better understand its impact. Observing functional and even structural brain changes over time, researchers may observe whether and more precisely how entrepreneurship education impacts the brain. Do such initiatives result in any changes whatsoever? Are changes in activation levels present in areas related to regions theoretically linked to entrepreneurship, such as the orbitofrontal cortex (uncertainty), nucleus accumbens (risk taking) or left inferior parietal cortex (creativity)? Do certain treatments or approaches, but not others result in significant changes in neural processing related to entrepreneurial behavior? How do neural responses to entrepreneurship education vary across individuals?

In sum, longitudinal neuroimaging data informing how the brain changes as a result of certain entrepreneurship education initiatives can offer new evidence on the impact of entrepreneurship education. Understanding how the brain itself responds to certain initiatives may assist in rethinking and refining how entrepreneurship education efforts are optimally approached.

CONCLUDING REMARKS

To the best of our knowledge, this work represents the first *cross-disciplinary* effort to bridge neuroscience and entrepreneurship. Given the emergence and increasing accessibility of neuroscience techniques, we argue that the time is ripe for the advancement of a neural-based understanding of the entrepreneurial process. The direct observation of brain activity brings into focus a fundamentally new level of understanding that can complement, challenge and ultimately extend present knowledge in entrepreneurship. In advancing a

foundation for research at the neuroscience-entrepreneurship intersection, we began this study by articulating how neuroscientific methods can add value to the field of entrepreneurship beyond existing approaches. We put forward an in-depth overview of two key methodologies with the intention of accelerating the learning curve for the entrepreneurship scholar. Moreover, we elaborated on a number of central areas of entrepreneurship cognition, and beyond, that could be meaningfully extended by neuroscience. We concluded with discussion of challenges that lie ahead. It has not escaped our notice that these efforts could serve as a cornerstone for the growth of a new sub-field within neuroscience and business, namely neuro-entrepreneurship.

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