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Electroencephalography (EEG) as a Research Tool in the Information Systems Discipline: Foundations, Measurement, and Applications

Gernot R. Müller-Putz
Graz University of Technology, gernot.mueller@tugraz.at

René Riedl
University of Applied Sciences Upper Austria and University of Linz

Selina C. Wriessnegger
Graz University of Technology

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Gernot R. Müller-Putz

Institute for Knowledge Discovery, Laboratory of Brain-Computer Interfaces, Graz University of Technology

gernot.mueller@tugraz.at

René Riedl

University of Applied Sciences Upper Austria and University of Linz

Selina C. Wriessnegger

Institute for Knowledge Discovery, Laboratory of Brain-Computer Interfaces, Graz University of Technology

Abstract:

The concept of neuro-information systems (neuroIS) has emerged in the IS discipline recently. Since the neuroIS field's genesis, several neuroIS papers have been published. Investigating empirical papers published in scientific journals and conference proceedings reveals that electroencephalography (EEG) is a widely used tool. Thus, considering its relevance in contemporary research and the fact that it will also play a major role in future neuroIS research, we describe EEG from a layman's perspective. Because previous EEG descriptions in the neuroIS literature have only scantily outlined theoretical and methodological aspects related to this tool, we urgently need a more thorough one. As such, we inform IS scholars about the fundamentals of EEG in a compact way and discuss EEG's potential for IS research. Based on the knowledge base provided in this paper, IS researchers can make an informed decision about whether EEG could, or should, become part of their toolbox.

Keywords: Brain, Construct, Electroencephalography (EEG), Error-related Negativity (ERN), Frequency Bands, EEG Guidelines, Neuron, NeuroIS, Spontaneous EEG, Event-related Potential (ERP), Measurement, Methodology, N200, N400, P200, P300, Research Method.

1 Introduction

The concept of neuro-information systems (neuroIS[1]) emerged in the course of the 2007 International Conference on Information Systems (Dimoka, Pavlou, & Davis, 2007, and is now contextually well defined (Riedl & Léger, forthcoming). Drawing on a definition put forward by a group of fifteen scholars (Riedl et al., 2010a), we define neuroIS as an interdisciplinary field of research at the nexus of neuroscience and IS research. In essence, neuroIS pursues two complementary goals. First, it contributes to an advanced theoretical understanding of the design, development, use, and impact of information and communication technologies (IT). Second, it contributes to the design and development of IT systems that positively affect practically relevant outcome variables (e.g., health, satisfaction, adoption, and productivity).

Since the neuroIS field's genesis, several neuroIS papers have been published. The first papers published in peer-reviewed IS journals appeared in 2010; specifically, they (Dimoka, 2010; Riedl, Hubert, & Kenning, 2010b) investigate research questions related to trust in online environments based on functional magnetic resonance imaging (fMRI). Moreover, recently, two mainstream IS journals, the *Journal of Management Information Systems* (Volume 30, Issue 4) and the *Journal of the Association for Information Systems* (Volume 15, Issue 10), published neuroIS special issues. Furthermore, many other papers have been published during the past years (see, e.g., a compilation at http://www.neuroIS.org/).

Investigating the empirical papers published in the two special issues reveals that many use electroencephalography (EEG). In the *JMIS* special issue, five out of six contributions applied EEG, and, in the *JAIS* special issue, two out of three studies employed it. It follows that, while different neuroscience tools such as fMRI (Dimoka, 2010; Riedl et al., 2010b; Riedl, Mohr, Kenning, Davis, & Heekeren, 2014a), hormone and enzyme assessments (Riedl, Kindermann, Auinger, & Javor, 2012; Tams, Hill, Ortiz de Guinea, Thatcher, & Grover, 2014), and measurements related to autonomic nervous system activation (e.g., heart rate (Astor, Adam, Jerčić, Schaaff, & Weinhardt, 2013; Ortiz de Guinea & Webster, 2013) or electrodermal activity (Léger, Riedl, & vom Brocke, 2014a; Minas, Potter, Dennis, Bartelt, & Bae, 2014; Riedl, Kindermann, Auinger, & Javor, 2013)) have also been applied in the field to some extent, EEG is the dominant method in contemporary neuroIS research. This finding is further substantiated by the fact that 25 percent of all papers that appeared in the proceedings of the *Gmunden Retreat* on *NeuroIS,* an academic meeting exclusively focused on neuroIS research, constitute investigations based on EEG[2].

We believe that EEG has dominated due to several factors acting in concert. As conceptual neuroIS papers outline (Dimoka et al., 2012; Riedl, 2009; Riedl et al., 2010a; vom Brocke, Riedl, & Léger, 2013), researchers typically select a research tool based on multiple factors, of which spatial resolution, temporal resolution, cost, and available knowledge base (i.e., literature dealing with the neural correlates of constructs relevant to the study, such as trust, emotion, technostress, or mental workload) have turned out to be key factors. Moreover, Riedl, Davis, and Hevner (2014b) discuss six factors critical for a neuroIS research methodology: reliability, validity, sensitivity, diagnosticity, objectivity, and intrusiveness of a measurement instrument. These six factors also affect which research tool researchers select. Thus, to explain EEG's current dominance in the neuroIS literature, it seems that EEG performs well on many of the mentioned factors, at least relatively, when compared to other neuroscience tools.

Of course, every research tool has strengths and weaknesses, and, therefore, a tool that outperforms all other tools on all possible selection criteria does not exist (for overviews that outline neuroscience tools' major strength and weaknesses, see Dimoka et al. (2012) and Riedl et al. (2010a)). Thus, applying one or another neuroscience tool always implies making trade-offs. For example, fMRI offers good spatial resolution (i.e., typically 1-2 mm millimeters). However, its application causes relatively high costs (i.e., a scanner usually costs up to USD$3,000,000, and, if access is rented, the costs per subject and hour can be $500 or more) and also requires a high degree of intrusiveness (i.e., participants are required to lie still on their back in the scanner while their head is restrained with pads to prevent head motion; the scanner is noisy)[3]. Moreover, fMRI's temporal resolution is poor because fMRI indirectly measures neural activity via hemodynamic processes (i.e., processes related to blood flow), and, hence, the measured signal does

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Note that author names on the first page are listed alphabetically.

[1] Please note that one can use either "neuroIS" or "NeuroIS" to refer to neuro-information systems. However, as a matter of style, *CAIS* does not capitalize field/discipline names.

[2] The proceedings are available at: *http://www.NeuroIS.org/.* The inaugural meeting took place in 2009, and proceedings are available since 2011. Period of analysis: 2011-2014.

[3] There is also a trade-off between authenticity and data quality in EEG research. For example, ideally participants are completely still in an EEG study, but this would diminish the authenticity of their interaction with an IT system.

not occur until a few seconds after stimulus onset. Other tools such as EEG have other strengths and weaknesses. As an example, when compared to fMRI, EEG offers excellent temporal resolution (milliseconds) and is less expensive (USD\$50,000-100,000 to acquire it (with that said, cheaper systems do exist); USD\$50 an hour per rental subject), and less intrusive (participants can sit in front of a computer and the tool does not cause noise). However, its spatial resolution is rather limited (typically ~1cm).

Considering the importance of EEG as a tool in contemporary research and that it will likely also play a major role in future neuroIS research, we describe EEG in layman's terms from a neuroIS standpoint. Since previous EEG descriptions in the neuroIS literature have only scantily outlined theoretical and methodological aspects related to this tool (typically, these descriptions are only a few paragraphs long; see, for example, Dimoka et al. (2012) and Riedl et al. (2010a)), the neuroIS literature needs such a description.

In essence, we inform IS scholars about EEG's fundamentals in a compact way. Based on this knowledge base, IS researchers can make an informed decision about whether EEG could, or should, become part of their toolbox. Moreover, based on a higher degree of familiarity, IS academics (i.e., editors, reviewers, and authors) can develop knowledge that is necessary to evaluate whether or not EEG is suitable to study a specific IS research question. Also, at least to some minimum degree, readers should be able to assess whether EEG is correctly applied methodologically. Thus, we seek to increase interest in EEG and neuroIS in general, and we provide initial knowledge that allows for researchers to evaluate EEG as a research tool in neuroIS. Also, our description will likely facilitate IS researchers' collaboration with EEG experts from other fields. However, it would be naïve to assume that reading an introductory paper such as the present one may substitute for both comprehensively studying more specialized literature and extensive hands-on training. In other words, becoming an EEG expert is likely to take several years of intensive theoretical and practical engagement. However, the first step is always the hardest, as a well-known proverb says, and, hence, we consider this paper as particularly useful for EEG novices.

EEG as a scientific tool has already existed for approximately 90 years (Hans Berger, a German physiologist, discovered a specific EEG-based brain wave in 1924 and published his findings in 1929). Hence, a large number of textbooks, book chapters, and journal papers have been published on EEG as a research tool in various scientific fields, such as medicine, psychology, biomedical engineering, and cognitive neuroscience. Also, many books and papers dealing with physiological aspects underlying the EEG signal and aspects related to acquiring and analyzing EEG data are available in many different fields. Against this background of highly fragmented and complex work that discusses EEG from many different viewpoints, we summarize selected, yet fundamental, aspects related to EEG that we believe are relevant for the IS scholar who is an EEG novice.

This paper proceeds as follows: in Section 2, we describe the physiological basis of the EEG signal. One needs to understand this basis because, without it, the IS scholar would not even know what kind of signal EEG actually measures. In Section 3, we describe the spontaneous EEG, event-related potentials (ERP[4]), and the major EEG frequency bands. In Section 4, we summarize methodological foundations of a typical EEG study and discuss selected aspects related to acquiring and analyzing data and how EEG studies should be reported in neuroIS publications. In Section 5, we outline EEG's potential in neuroIS research. To this end, we focus on important EEG measures. Specifically, we show that the two major brain wave types described in the EEG literature are relevant in IS research; namely, the spontaneous EEG (signals resulting from regular brain activity without perception of an experimentally manipulated stimulus) and the event-related potential (ERP, signals reflecting activity from synchronously active populations of neurons that either occur in preparation for, or in response to, discrete events that are experimentally manipulated). Finally, in Section 6, we conclude the paper.

Before we describe EEG's physiological foundations, note that we solely deal with scalp-recorded EEG, and, hence, we do not cover intracranial EEG, where electrodes are directly placed below the dura mater near the surface of the brain to measure electrical activity of the cerebral cortex, which is known as electrocorticogram (ECoG). We refer readers interested in ECoG to Crone et al. (2006), Jacobs and Kahana (2010), Lachaux, Rudrauf, and Kahane (2003), and Miller et al. (2007).

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[4] Throughout this paper, we also use the acronym ERP to denote the plural (i.e., event-related potentials).

2   Physiological Foundations

2.1   The Neuron

The neuron is the core element of the nervous system. A neuron is an electrically excitable nerve cell that receives, processes, and sends information. However, a neuron's operation is not only based on electrical impulses. Rather, communication with other neurons occurs through chemical signals. As Figure 1 shows, a typical neuron comprises a cell body (soma), dendrites, and an axon. Information processing takes place in the soma, receipt of information occurs via dendrites, and an axon sends information. A cell body usually has many dendrites but only one axon. As the arrows in Figure 1 illustrate, information is conveyed to dendrites via an axon, and at the end of an axon are terminal buttons that receive electrical signals and then release chemical substances to the synapse (these substances are referred to as neurotransmitters). The neurotransmitter molecules are the basis for information transmission from one neuron to another one, where receptors exist for specific neurotransmitter molecules (see Figure 1).

For mental processes, such as those relevant in IS research (e.g., trust, decision-making), to emerge, networks of neurons must be active. Such networks are referred to as neural networks, and the human brain is estimated to comprise 100 billion neurons, with each neuron having approximately, on average, connections to 10,000 other neurons.
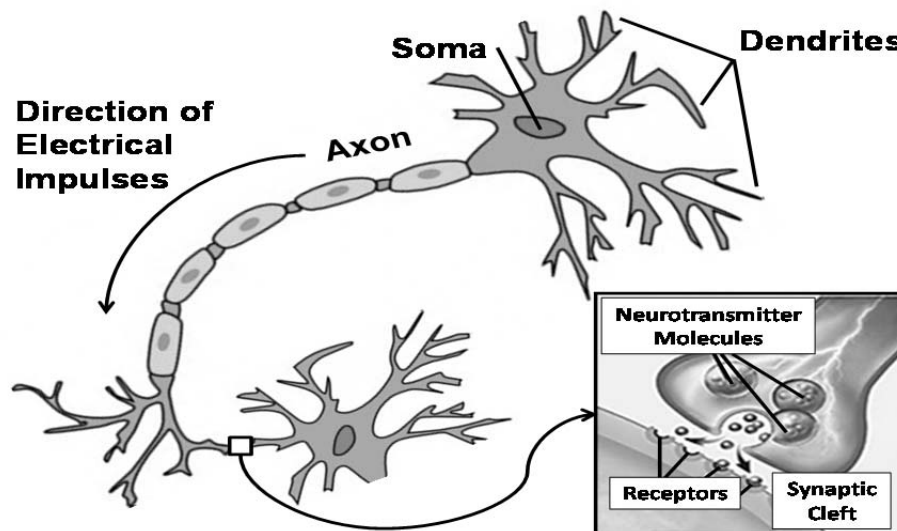

Figure 1. Neuron and Information Transmission via a Synapse

EEG oscillations are the manifestation of the activity of populations of neurons in the brain. One can record this activity on the surface of the scalp with electrodes (the tissue between the neural source of the EEG and the scalp acts as a volume-conductor). Volume conductor models are the basis for source analysis in EEG (Okada, 1993). Reconstructing current distributions from measured surface fields is called the inverse problem. Its solution requires simulating the field distribution for a current dipole in the corresponding volume conductor by using the quasi-static Maxwell equations, also known as "forward problem". To understand the relationship between EEG and the underlying primary source configuration, the human head's electrical conduction properties (the volume conductor) have to be modeled. The progress made in developing forward modeling techniques has led to a variety of source analysis applications (Makeig et al., 2002). In the past decades, researchers have developed better source localization techniques that are robust to noise and well informed by anatomy, neurophysiology, and more realistic volume conduction models (Liu, Dale, & Belliveau, 2002; Wolters, Grasedyck, & Hackbusch, 2004).

2.2   Summation of Post-synaptic Potentials

Electrical activity that results from activation of any particular neuron is very small, and, hence, it is only possible to measure the collective activity of a large number of neurons at the scalp (Fabiani, Gratton, & Federmeier, 2007). Researchers hypothesize EEG oscillations recorded on the scalp to be the outcome of

the summation of excitatory and inhibitory post-synaptic potentials in cortical pyramidal neurons. Researchers have estimated that tens of thousands of synchronously activated pyramidal cortical neurons are involved for an EEG oscillation to emerge (Pizzagalli, 2007; Speckmann, Elger, & Altrup, 1993). The orientation of the neurons' dendritic trunks in a parallel way to each other and perpendicular to the cortical surface results in summation and propagation to the scalp surface. To sum up, two specific requirements must be met for an EEG oscillation to emerge (Fabiani et al., 2007): 1) neurons must be active synchronously, and 2) the electric fields that result from neurons' activation must be oriented in a specific way so that the effects can cumulate[5].

With respect to the orientation of the neural fields, Lorente de Nò (1947) was the first to distinguish between open fields and closed fields[6]. However, only structures with some degree of open-field organization generate EEG oscillations that can be recorded at the scalp, which is primarily the case in most parts of the cerebral cortex (i.e., the outermost layered structure of neural tissue in the human brain). From an electrical viewpoint, these parallel neurons form an electrical dipole (because many of the cells receive input from post synaptic potentials synchronously). The larger the number of cells is, the higher the potential deflection in the EEG is. In contrast, in structures with a closed-field organization (e.g., amygdala), neurons' electric fields are typically oriented in different directions, which impedes the summation process (i.e., they cancel each other out). Thus, such structures do not generate large summated dipoles that are evident at the scalp (Bartholow & Amodio, 2009). It follows that activity from such structures (e.g., activity in subcortical structures like the amygdala) cannot be assessed by EEG oscillations at the scalp.

Considering EEG's physiological foundations that we have outlined so far, an important implication for correctly interpreting EEG research emerges. EEG oscillations recorded at the scalp only represent a subset of the brain's electrical activity at a particular point in time. The consequence of this fact has been tellingly described by Fabiani et al. (2007, p. 88), who write with respect to ERP studies that:

> It is entirely possible that a sizeable portion of the information processing transactions that occur after (or before) the anchor event is "silent".… For this reason, some caution should be used in the interpretation of ERP data. For instance, if an experimental manipulation has no effect on the ERP, we cannot conclude that it does not influence brain processes. By the same token, if two experimental manipulations have the same effect on the ERP, it cannot be concluded that they necessarily influence completely identical processes.

As we mention above, EEG oscillations recorded at the scalp have their origin in post-synaptic potentials occurring in large clusters of neurons. Due to the fact that the area of an electrode (the diameter is ~1cm) covers an estimated 250,000 neurons (Baillet, Mosher, & Leahy, 2001), a large number of neurons must be synchronously activated to detect EEG oscillations at the scalp. Importantly, neural assemblies of both neighboring and distant brain regions may exhibit substantial synchronization, which contributes to the emergence of a measurable EEG signal (referred to as local-scale and large scale synchronization, respectively). Hence, synchronized oscillations are regarded as a major mechanism for communication among neurons that are spatially distributed across the brain, and this mechanism determines neural networks' emergence (Pizzagalli, 2007). Research indicates that low-frequency oscillations (e.g., theta, Table 1) span larger neural populations and that higher-frequency oscillations (e.g., gamma, Table 1) span smaller neural assemblies (Buzsaki & Draguhn, 2004). From a neuroIS viewpoint, this finding is crucial because the neural implementation of various mental processes relevant to IS research (often highly complex cognitive processes; e.g., trust) requires large scale synchronization (i.e., a network of spatially distributed brain regions is active). One typically investigates large-scale neural synchronization based on EEG coherence analysis (Pizzagalli, 2007), an advanced method in EEG research (see Section 4.4).

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[5] Physiologists and neuroscientists have long speculated about the likely sources of scalp-recorded EEG oscillations. As we mention above, today it is an established fact that EEG oscillations are most likely the result of the summation of post-synaptic potentials of a large number of synchronously activated (or inhibited) neurons. Thus, EEG oscillations are *not* the outcome of the summation of action potentials (i.e., pre-synaptic potentials) primarily because these potentials have a short duration, which negatively affects the summation process. Unlike action potentials, post-synaptic potentials have a relatively slower time course and are more likely to act synchronously, which affects the summation process positively (Allison, Wood, & McCarthy, 1986; Fabiani et al., 2007). Harmon-Jones and Peterson (2009) indicate that an action potential's duration is approximately 1 millisecond, while post-synaptic potentials' duration is tens or even hundreds of milliseconds.

[6] Open-field organization describes a state in which neurons are ordered so that their dendritic trees are all oriented on one side while their axons all depart from the other side. This state causes the electric fields to orient into the same direction and summate. Generally, open-field organization occurs whenever neurons are organized in layers (Fabiani et al., 2007).

Gevins and Smith (2007) outline five major determinants of the degree to which potentials arising in the cortex are measureable at the scalp: 1) amplitude of the signal at the cortex, 2) size of the region over which post-synaptic potentials occur synchronously, 3) proportion of cells in that region that are in synchrony, 4) location and orientation of the activated cortical regions in relation to the scalp surface, and 5) amount of signal attenuation and spatial smearing generated by conduction through the skull and other tissue layers.

3   Spontaneous EEG, Event-Related Potentials (ERP), Frequency Bands

In Section 1, we indicate that EEG research distinguishes between two major brain wave types: spontaneous EEG (also referred to as continuous EEG) and ERP (also referred to as evoked potential (EP)). The spontaneous EEG is the measurable part of brain activity that goes on permanently in the living individual. This kind of brain wave type is generally referred to as the encephalogram and simply constitutes the measurement of electrical signals in a time window. In the healthy waking brain, the peak-to-peak amplitude of this scalp-recorded signal is typically under 75µV but sometimes also goes up to 100µV (microvolts, one millionth (10^{-6}) of a volt, the unit of electric potential) (Gevins & Smith, 2007; Ramsoy, Balslev, & Paulson, 2010). A considerable portion of the signal power originates from rhythmic oscillations in a frequency bandwidth from below 1Hz to approximately 40Hz (Hertz is the unit of signal frequency and indicates cycles per second), even though higher frequencies are also possible (Gevins & Smith, 2007; Schomer & Lopes da Silva, 2011)[7]. Healthcare professionals measure spontaneous EEG extensively in clinical contexts (e.g., to diagnose epilepsy). However, this brain wave type is also relevant in cognitive neuroscience, psychophysiology, and neuroIS, among other fields.
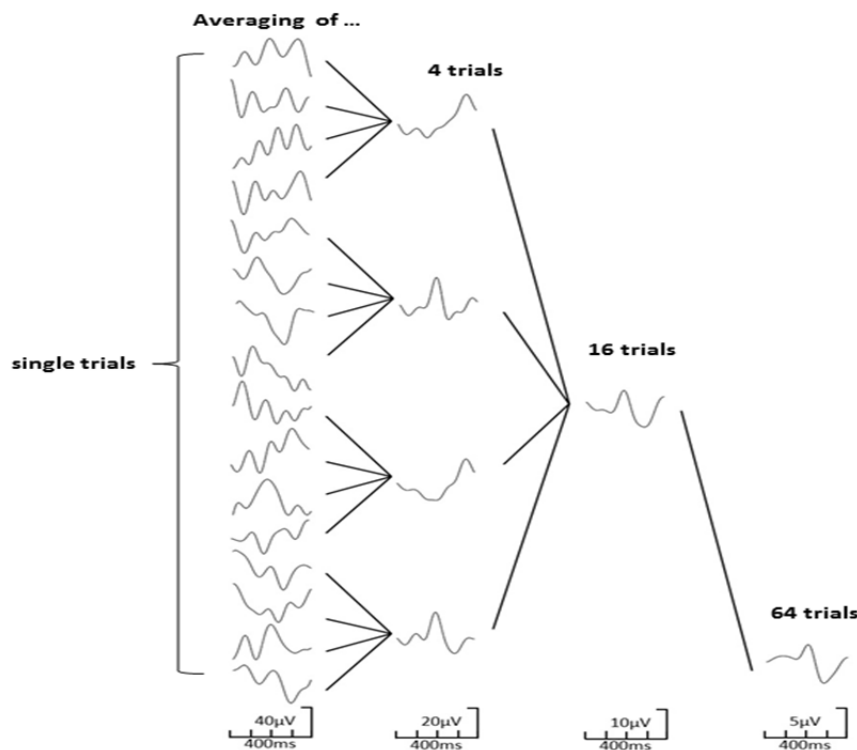
Note: averaged waveform of a typical ERP. First column: 16 single trial ERPs. Second column: average ERPs computed across 4 trials. Third column: average ERP computed across 16 trials. Fourth column: average ERP computed across 64 trials.

Figure 2. Effects of Successive ERP Averaging (Adapted from Bartholow & Amodio, 2009)

Event-related potentials (ERP) originate from specific (experimentally manipulated) external stimuli (that are designed to become perceivable by the participant at an exactly specified time point). These stimuli can be, for example, visual, auditory, somatosensory, or even olfactory. Importantly, ERP signals are

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[7] Note that in case of invasive measurement on the surface of the brain (intracranial EEG), the amplitude is about 1-2 mV (millivolts, one thousandth (10^{-3}) of a volt).

typically not very strong, and, hence, it is difficult to distinguish them from the spontaneous EEG in raw data. However, a standard procedure exists in EEG research to make the effects of stimuli visible (namely, via repeated exposure to the stimulus and averaging of the EEG responses). Because aspects of the EEG that are not time-locked and not phase-locked to the stimulus are assumed to vary randomly from sample to sample (such as uncorrelated noise), averaging a repeated measurement increases the signal-to-noise ratio, which makes the ERP visible (Fabiani et al., 2007; Luck, 2005; Regan, 1989).

The signal-to-noise ratio (SNR) increases by the square root of the number of trials (N) included in an average but only if three conditions are met: 1) signal strength is constant over trials; 2) noise is random across trials, with a mean of zero and constant variance over trials; and 3) signal and noise are uncorrelated. Formally, SNR (dB) = $20*\log(\sqrt{N}*U_{Signal}/U_{Noise})$. However, note that Fabiani et al. (2007) indicate that the three conditions may not always be met in a typical psychophysiological experiment, which must be considered in neuroIS EEG research.

The EEG reflects many thousands of simultaneously ongoing brain processes, and the neural response to a specific stimulus is usually masked by direct EEG measurement. Therefore, in EEG recording situations, it is difficult to observe an ERP after the presentation of one single stimulus. The ERP only become visible when many individual neural responses to target stimuli are averaged (see Figure 2). With this technique, the noise in the data is reduced, and only the voltage response in relation to the stimulus is enhanced.

Figure 2 illustrates the concept of averaging based on an example taken from Bartholow and Amodio (2009). The illustrated ERP waveforms are based on measurements taken from four subjects during an auditory discrimination task. For each of these individuals, four individual trial waveforms (first column), representing the response to four presentations of one and the same stimulus, are averaged to calculate individual average waveforms (second column). Moreover, these waveforms are averaged to form a grand average waveform (third column), which represent the average response to this stimulus across the four participants. Importantly, adding responses of more subjects or more responses per subject leads to a cleaner ERP signal with less random EEG noise (fourth column).

In EEG research, specific frequency bands have certain names (Schomer & Lopes da Silva, 2004). Table 1 summarizes EEG frequency bands and their corresponding frequency bandwidth and major associated mental states[8]. Moreover, the table provides example illustrations of the EEG that we developed with MATLAB simulations. These illustrations show that, generally, low frequencies (delta and theta) exhibit large synchronized amplitudes and that high EEG frequencies (beta and gamma) exhibit small amplitudes because the degree of desynchronization in the underlying neural activity is high; alpha is in between (Pizzagalli, 2007).

Delta waves are characterized by very low-frequency activity (1-4Hz) usually related to deep and unconscious sleep in healthy humans. The amplitude of this wave is typically between 20 and 200 µV. This wave type is also associated with pathological neural states, such as loss of consciousness or coma. Generally, delta activity diminishes with increasing age, which suggests that this activity is primarily an inhibitory mechanism (Hobson & Pace-Schott, 2002).

Theta waves are characterized by low-frequency activity (4-8Hz) typically associated with specific sleep states, mediation, and drowsiness. However, in addition to this first type of theta activity, another important type is described in the literature, which is referred to as frontal midline theta. This second type has been related to mental effort, which suggests focused attention on a stimulus at hand. The amplitude of this wave is typically between 8 and 10 µV (Cahn & Polich, 2006).
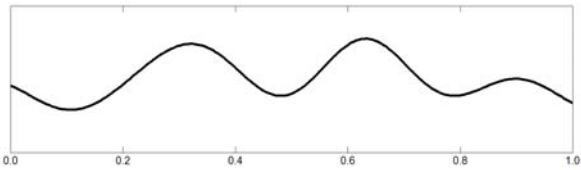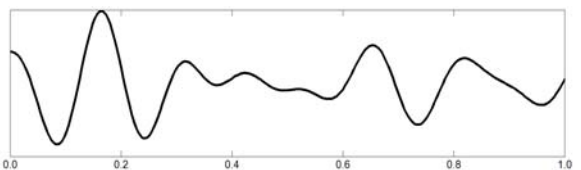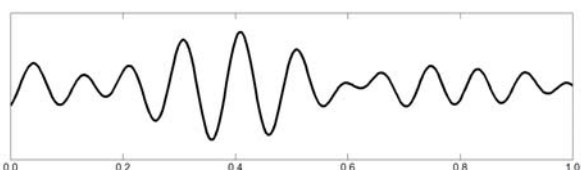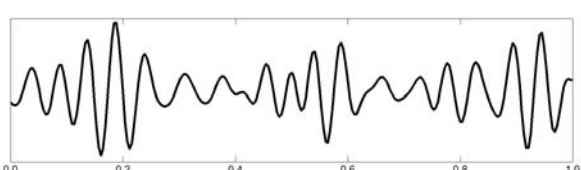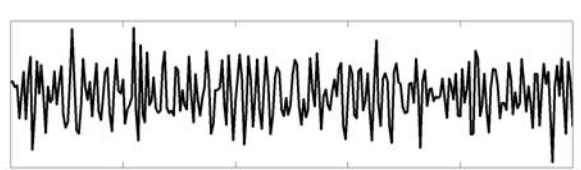
Alpha waves are characterized by medium-frequency activity (8-13Hz) and generally indicate states of relaxed wakefulness in healthy adults (Berger, 1929). The amplitude of this wave is typically between 20 and 200 µV. This wave type is also common during resting periods in which people have their eyes closed. Based on this finding, researchers have argued that alpha waves constitute a neural correlate of cognitive inactivity, also referred to as cortical "idling" (Pfurtscheller, Stancak, & Neuper, 1996). However, studies with evoked EEG activity (i.e., ERP investigations) have found that alpha waves may indicate different forms of information processing in which different alpha sub-bands (e.g., 8-10Hz and 10-13Hz) subserve different functional processes (Klimesch, 1999; Niedermeyer, 1997).

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[8] Please note that the exact thresholds of these frequency bands vary in the scientific literature and, hence, are, at least to some degree, subject to debate (Schomer & Lopes da Silva, 2004).

Beta waves are characterized by high-frequency activity (13-25Hz) related to various mental states, such as active concentration, task engagement, excitement, anxiety, attention, or vigilance. The amplitude of this wave is usually between 5 and 10 µV. Beta activity primarily constitutes an excitatory mechanism (Pfurtscheller & Lopes de Silva, 1999).

Gamma waves are characterized by very high-frequency activity (25-200Hz, but typically not much higher than 40Hz during mental activity in healthy humans). This wave is often associated with arousal and perceptual binding mechanisms (i.e., integration of various aspects of a stimulus into a coherent overall perception). The amplitude of this wave is usually between 1 and 2 µV (Hughes, 2008).

Table 1. EEG Frequency Bands

Frequency band	Bandwidth	Associated mental states	Example illustration
Delta	1-4Hz	Deep sleep, coma	
Theta	4-8Hz	Specific sleep states, mediation, drowsiness	
Alpha	8-13Hz	Relaxation, readiness	
Beta	13-25Hz	Active concentration, anxiety, focused attention	
Gamma	25-200Hz	Arousal, peak performance	

4   Methodological Foundations

In this section, we outline major methodological foundations of an EEG study. Specifically, we summarize aspects that are important in the context of a neuroIS investigation. Note that, in an introductory paper such as ours, one must be selective in its describing the various aspects related to planning and conducting an EEG study. It is impossible to summarize detailed results of decades of methodological EEG research in a tutorial. Hence, IS scholars who plan to use EEG are advised to read more specialized literature, particularly guideline papers on data acquisition and signal analysis, such as Davidson,

Jackson, and Larson (2000), Gasser and Molinari (1996), Handy (2005), Luck (2005), Nuwer et al. (1999), and Pivik et al. (1993).

4.1   Recording the Signal

EEG signals reflect the difference in voltage between two electrodes: an active electrode and a reference electrode. Thus, the selection of the reference determines EEG waveforms. As an example, recording with a vertex (Cz) reference (see Figure 3) results in small EEG deflections in the proximity of Cz (because synchronization of physiological activation in closely spaced brain areas takes place), while deflections are likely to be larger in areas more distant to Cz (Pizzagalli, 2007). Also, it is possible to record differences in voltage between two active electrodes, referred to as "bipolar derivation" (Rippon, 2006). Essentially, reference electrodes are never completely electrically inactive, a fact that is independent of whether a reference is cephalic and noncephalic (e.g., earlobes). Making the decision about the reference electrode is important primarily because noncephalic activity (e.g., eye movements, facial muscles, or heart beats) may contaminate EEG signals. However, even though the selection of the reference electrode affects EEG waveform analysis, reference choice is not relevant for source localization (i.e., to determine from which areas in the brain the scalp-recorded signals come from) (Pizzagalli, 2007). Generally, a first step after EEG recording is to preprocess data in a way that it becomes "reference free"[9]. One approach calculates a common average reference (the mean of all EEG channel time series) where each single channel is referred to afterwards. Another established method to increase spatial resolution and to eliminate the influence of reference electrode distortions is to calculate Laplacian derivations. This method substracts the average signal from the four orthogonal electrode sites from the electrode of interest in the middle of these four electrodes. This procedure increases the EEG's spatial resolution. Importantly, the distance to the four electrodes must not differ (Hjorth et al., 1975)[10].

In EEG research, electrode locations are based on standards. Originally, the 10-20 system proposed by Jasper (1958) was the accepted system. Here, electrodes are placed at sites 10 percent and 20 percent from four fiduciary points; namely, nasion, inion, left, and right mastoids. However, this standard has been advanced, and systems such as the 10-10 or 10-5 have been developed in which intermediate positions between those of the original 10-20 system have been derived (Pizzagalli, 2007). Figure 3 shows electrode positions and corresponding labels in three different systems: the original 10-20 system (black circles), the 10-10 system (gray circles indicate additional positions), and the 10-5 system (additional positions are indicated with dots) (Oostenveld & Praamstra, 2001, p. 716). Note that Figure 3 also shows a selection of additional positions useful for a 128 channel EEG system (see the open circles). Also, Figure 3 illustrates that a naming convention for electrode positions exists in EEG research. The convention is as follows: the first letter refers to the brain region over which the electrode is placed (Fp = frontal pole, F = frontal area, C = central area, P = parietal area, T = temporal area, and O = occipital area). Electrodes in between these regions are labeled by using two letters (e.g., FC = frontal-central). A number (e.g., F7) or another letter (e.g., Cz) follows after the first letter. Odd numbers indicate sites on the head's left side and even numbers indicate sites on the right side. Moreover, numbers increase as distance from the head's midline increases (see, for example, F1 and F9 in Figure 3, and note that the latter is farther from the midline than the former). As Figure 3 also outlines, the letter z is used to indicate the midline.

In EEG research, oscillations are usually recorded from 32, 64, 128, or 256 electrodes (channels) even though a smaller number is possible (see, e.g., the summary of a brain-computer interaction project in Riedl et al. (2010a, pp. 251-252)). In this context, the number of electrodes has an influence on spatial filtering approaches and source reconstructions. Evidence indicates that improved spatial resolution (i.e., where in the brain is activation taking place) can be achieved with more electrodes; yet, the relationship is not linear. Specifically, Lantz, Grave de Peralta, Spinelli, Seeck, and Michel (2003) report that source localization accuracy increased linearly from 25 to 100 electrodes but reached a plateau at this number and, therefore, accuracy no longer increased with additional electrodes. Also, note that the number of electrodes has an effect on topographical mapping of ERP components.

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[9] Note that positioning of the recording reference is sometimes dependent on the hardware and not modifiable.
[10] It is possible to re-reference EEG data "offline" and, thus, change the reference used during the recording of the EEG data. Also, we indicate that a common average reference is based on the premise that the head is a perfectly round sphere and that all points on the head are measured. Thus, it should not be performed with too few electrodes. Moreover, one should not directly compare the results of studies that use different references.

Today, researchers often mount the electrodes in a stretch lycra cap where they are positioned over the entire scalp surface. Generally, a uniform distribution of the electrodes on the scalp is essential. Electrodes are often made of tin (Sn), silver (AG), or silver chloride (AgCl). In order to reduce electrode impedances, electrode sites have to be abraded, and conductive gel is used as a medium between the electrodes and scalp. However, today, using systems that do not require scalp abrasion prior to applying the electrodes is also not unusual (e.g., based on electrolyte-soaked sponges) and offers practical advantages such as reduced electrode application time or reduced discomfort of participants (Harmon-Jones & Peterson, 2009). Water-based and dry electrodes that improve user comfort enormously (e.g., hair wash is no longer needed or short montage time) are also available today. Moreover, increasingly more EEG systems have nonmetallic electrodes (e.g., carbon and carbon fiber); this property makes systems compatible with the requirements of other imaging technologies such as fMRI (Rippon, 2006) because EEG equipment must not be metallic if used simultaneously in an MRI machine. Moreover, note that caps often contain a ground electrode, which is connected to the isoground of the amplifier and assists in reducing electrical noise. A typical EEG study also records eye movements (electrooculography, EOG) to reduce noise in the EEG signal (Harmon-Jones & Peterson, 2009) because signals originating in eye movements may significantly distort brain potentials.
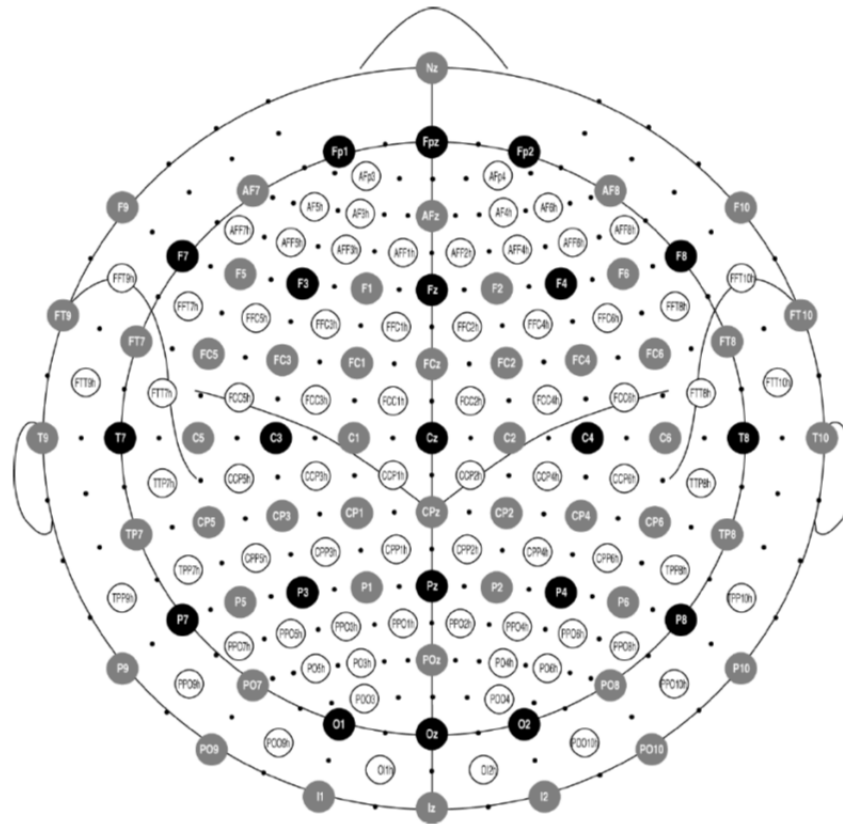
Figure 3. Electrode Positions in EEG Research Based on Different Systems
(Oostenveld & Praamstra, 2001, p. 716)

Technically, electrodes are connected to (pre)amplifiers, including hardware filters, to improve the signal-to-noise ratio, and the outputs of the amplifiers are converted to numbers by an analog-digital converter. Amplifiers magnify the basically weak electrical signals emitted by the neurons by a factor of 10,000-50,000, so that they can be measured accurately (Bartholow & Amodio, 2009). Generally, the signals are sampled at a frequency of at least 100Hz (sampling rates of 250-1000Hz are common) and are then stored in computer files for subsequent analysis (Bartholow & Amodio, 2009; Fabiani et al., 2007) or are processed online and in real-time to provide feedback or to control a certain application such as in brain-computer interfacing (Müller-Putz et al., 2011; Müller-Putz, Scherer, Pfurtscheller, & Rupp, 2005).

The extent to which the digital signal at hand accurately reflects the analog (neuronal) signal depends on the sampling rate. Generally, the sampling rate should be at least twice the highest frequency present in the signal under investigation. This rule is known as the Nyquist theorem. Not considering this theorem may lead to introducing spurious low-frequency components into the signal, a phenomenon referred to as aliasing (because the reconstructed signal is considered as an alias of the original signal). In essence, aliasing occurs when a signal is sampled at a rate that is too low, which results in irreparable distortion of the digital waveform (Pizzagalli, 2007). Consider the following example: if one is interested in frequencies below 40Hz, then at least 80 samples per second should be collected. Why? According to the Nyquist theorem, one can exactly reconstruct a continuous signal from its samples only if the signal is sampled at least twice as great as the actual signal bandwidth. If this requirement is not met, frequencies will overlap and data becomes unusable (Gratton, 2007; Harmon-Jones & Peterson, 2009; Luck, 2005). Note, however, that the mentioned example relies on a perfect filtering at 40Hz. However, such perfection is not possible since filters built in EEG amplifiers have a dampening between 20dB and 80dB per decade. More practical would be to have sampling frequency about 4 to 5 times higher than the highest signal of interest; in our example, this would imply a sampling frequency of 200Hz.

Another important aspect related to signal recording is that the ERP is small if compared to the continuous EEG (the former typically has a few microvolts (μV), while the latter usually has about 50μV). Hence, in case of running an ERP study, procedures must be applied to discriminate the ERP signal from the continuous EEG. Fabiani et al. (2007) indicate that averaging samples of the EEG that are time-locked to repeated occurrences of the event under investigation (in a neuroIS study, for example, a pop-up message on a user interface) is the most common procedure for signal discrimination. Note that averaging works because aspects of the EEG that are not time-locked to the event are assumed to vary randomly from sample to sample, and, therefore, this procedure leads to a reduction of noise, which makes the signal under investigation (more) visible. The resulting voltage × time function contains several positive and negative peaks that form the basis for multiple statistical operations (Fabiani et al., 2007) (we describe data analysis in more detail in Section 4.4).

4.2   Interacting with the Participant

In EEG research, considering the possible negative effects of social interaction between the experimenter and the participant is particularly important. Cacioppo, Petty, and Marshall-Goodell (1985, p. 288), pioneers in the psychophysiology field, stress that evaluation apprehension (i.e., participant apprehension about being evaluated by the experimenter) and demand characteristics (participants try to discern the true purpose of the study and shape their behavior accordingly) play a major role in studies based on neurophysiological measurement. However, they also indicate that one can minimize these issues by employing several techniques. First, giving the subject a false hypothesis is essential. Moreover, emphasizing (e.g., based on a cover story) that the biological mechanisms being investigated are not subject to voluntary control is also important. Also, designing a setting and experimental procedure that minimizes the subject's feeling of being scrutinized may positively affect research results. Finally, among other techniques, reducing the difference in status between the experimenter and participant is essential (e.g., through establishing rapport). In essence, Cacioppo et al. (1985) indicate that the nature of the interaction between the experimenter and study participant is both a source of biases but, at the same time, the source of their solutions. Obviously, neuroIS researchers should consider this finding to maximize the scientific value of their investigations.

While the techniques that Cacioppo et al. (1985) describe refer to psychophysiological research in general, other scholars have outlined specific guidelines for different neuroscience methods. For example, the Graz BCI lab (http://bci.tugraz.at/) has a standardized EEG protocol. In this section, we briefly describe this protocol (steps 1 through 5). However, we emphasize that protocols may differ between research labs.

1.   **Recruitment of subjects***:* to test new paradigms or the effectiveness of new training strategies or feedback versions, one often needs to recruit naïve subjects. If the person has not participated in any prior EEG experiment, one needs to provide them with general information about the non-invasive method and procedure of EEG recording during the recruitment (e.g., via telephone or face-to-face). Subjects should be told that the entire procedure of such an EEG recording is completely free of pain and that they will experience no side effects as a result of participating in the experiment. The only potential annoyance is the residue of electrode paste, which can be removed by washing the hair after the experiment.

Furthermore, the duration of each experiment should be clarified prior to participation. Persons who are not interested in the topic and/or willing to participate in such experiments over a longer period should not even be invited for a test measurement. In the case of BCI training, the individual should be available for a certain number of weeks, and researchers should pay special attention to the subject's individual time schedule when arranging an appointment. Furthermore, subjects should generally meet the following criteria: no neurological disease (e.g., epilepsy) if that disease is not the object of the investigation, no attentional disorder, normal or corrected-to-normal vision, handedness should be kept constant over subjects, and the examiner should ensure that the subject can understand the instructions (language). Informing the subjects (who meet the mentioned criteria) that a monetary reward will be provided to them for their participation has turned out as a useful incentive to ensure that individuals perform "enthusiastically" during the experiments.

2. **Montage of electrodes***:* initially, the chest belt must be fixed around the subject's chest. The electrode cap should be fixed at such a chest belt to avoid the cap's shifting during the measurement. If the experiment (e.g., in case of a monopolar derivation) requires the montage of a reference electrode, the electrode should be fixed on a mastoid before putting on the electrode cap. The cap's correct position should be measured in accordance with the international 10-20 system (see Figure 3). Thus, the distance between nasion and inion and between the preauricular points should be sized. The center of both distances belongs to the electrode position Cz. After fixing the cap on the chest belt, the required electrode positions should be cleaned with an Abralyt (electrode paste) to remove dead dander. It is important to use electrode paste that is adequate for the electrodes (the company selling the electrodes typically provides this information). The electrode gel consists of pumice stone and has to be used to obtain good contact between the scalp and the electrodes. In case of good contact, low impedance exists, which is crucial because EEG signals are weak (in a range of a few microvolts) and also susceptible to interference. Cleaning should be done with caution because the pumice stone as one ingredient grinding on one position for a long time can lead to pain. Once cleaning is finished, the electrodes can be attached to the sites provided. To avoid a short circuit (e.g., caused by too much Abralyt), the electrode paste should be used carefully. EEG data is usually derived from the scalp with gold or silver/silver-chloride electrodes. After fitting the montage of electrodes on the subject, one needs to check the impedance, which should reach a value of about 5kΩ or lower. A low impedance value is necessary to keep the signal to noise ratio as low as possible. One should also record at least one bipolar EOG-channel to control eye blinks and eye movements during the experiments and to ensure correct artifact correction in further analyses.

3. **Environmental conditions during EEG experiments***:* the investigator has to control the following environmental and other conditions during the entire study to reduce their influences on the results: 1) dim the illumination of the laboratory (note that illumination affects the alpha rhythm), 2) reduce noise to a minimum, 3) ensure other people do not disturb, 4) ensure the temperature is comfortable, 5) consider adequate length of breaks between runs, 6) assure subjects' wellbeing, 7) pay subjects, 8) maintain personal contact with the subject, and 9) encourage subjects to keep motivation high.

4. **Instructions to the participant***:* researchers should present subjects with instructions about the experiment in written form (to ensure a standardized procedure) after electrode montage while the investigator is plugging the electrodes into the amplifier.

5. **Post-experiment questionnaire***:* after the experiment, it can be useful to conduct a short interview with the subject (or to use a questionnaire). Data can be collected on multiple aspects related to the experiment, including the subjective rating of the subjects' performance, progression of concentration over the runs, or subjects' wellbeing during the sessions.

We hope this brief description gives an impression of both the effort to prepare a participant for an EEG study and the relevance of the experimenter's interaction with the participant for research results. Moreover, we stress that the procedures to prepare a participant significantly depend on the specific EEG system used. In particular, increasingly more EEG systems offer wireless technology where electrodes can be directly placed on the head without applying gel or electrolyte-soaked sponges (referred to as "dry electrodes"), and, often, these systems are based on a relatively small number of electrodes (e.g., 8, 16, or 32 channels). Intentionally, we do not indicate specific products or firms here.

4.3   Dealing with Artifacts

It is impossible to record EEG without any contamination, and, hence, researchers must carefully consider artifacts in EEG studies. Generally, biological and non-biological artifacts exist (Harmon-Jones & Peterson, 2009; Pizzagalli, 2007). Major sources of biological artifacts are participants' muscle activities (e.g., face), eye blinks and eye movements, and heartbeat. Thus, concurrent recording of the electromyogram (EMG), electrooculogram (EOG), and electrocardiogram (ECG) are crucial for detecting and/or removing these artifacts. Major sources of non-biological artifacts are primarily external electrical noise coming from power lines, electric lights, or computers; poor subject grounding, poor electrode contact, and cable movements are further examples. Major countermeasures for non-biological artifacts include shielding the recording system, using filters (e.g., notch filters to remove electrical noise), and properly grounding subjects (Harmon-Jones & Peterson, 2009; Pizzagalli, 2007).

As for constructing and arranging space in EEG laboratories, Bartholow and Amodio (2009) indicate that such laboratories often include two separate rooms. One room is used to collect the data (i.e., the room in which the experimenter conducts the actual experiment with subjects). Essentially, this room, often referred to as participant chamber, should be electrically shielded and soundproofed to avoid potential artifacts in the data. The second room is the control room in which the experimenter can observe the data acquisition process. It is important that hardware (e.g., amplifiers and computers) is located in the control room and not in the participant chamber, which helps avoid artifacts.

As we mention above, one cannot obtain data that is completely free of artifacts. Thus, artifacts must be detected. Both visual and automatic (offline) artifact detection is important before one actually analyzes data, including testing hypotheses. Pizzagalli (2007) indicates that, when one visually inspects data, "substantial expertise is required for a proper differentiation of normal and contaminated EEG activity" (p. 63). It follows that EEG novices should apply automatic artifact detection. However, as experience increases, visual artifact detection may become a complementary option to automatically detecting artifacts.

Fabiani et al. (2007) provide general guidelines on how to handle artifacts: first, care should be taken to set up a recording situation so that artifacts are minimized (factors to consider are, for example, choice of the recording environment, electrode locations, and experimental task). Second, it is possible to discard trials that contain artifacts.

In case that one takes high-density recordings (e.g., 128 electrodes), one can remove artifact-contaminated sites and interpolate missing data from artifact-free electrodes. However, this technique may lead to biased results. Third, as we indicate above, one can measure the extent of the artifact and then remove it from the data. This technique has been used frequently to handle ocular and sometimes also muscle artifacts. Fourth, one can use filters to attenuate artifactual activity. This technique particularly holds value when the frequency of the artifactual activity is outside the frequency range of the EEG signals of interest. In the rest of this section, we elaborate on the third and fourth point.

Removing muscle and ocular artifacts (among others) is important in EEG studies (others include ECG with a range of 1-1.5Hz). EMG signals (originating from muscle activity) are typically within 20 and 1000Hz. Thus, muscle activity has the potential to contaminate several EEG frequency bands (see Table 1). Pizzagalli (2007) argues that contamination from muscle activity can be particularly problematic for studies interested in gamma activity (25-100Hz, typically 40Hz), and he writes that "[c]onsidering the explosion in interest in the functional role of gamma activity in mental processes, it is clear that proper attention must be devoted to the issue of EMG contamination to the gamma band" (p. 65).

Importantly, as a result of this significant frequency overlap, removing muscle artifacts through filtering distorts the actual brain-derived EEG signals. Based on a brief review of scientific literature, Pizzagalli (2007) summarizes approaches to deal with the issue. In essence, he summarizes two major approaches. First, regression approaches take activity in higher frequencies (e.g., > 50Hz) as a marker of muscle artifact to remove its variance; also, it is possible to enter it as covariate in analyses of variance (ANOVA). Second, independent component analysis (ICA) has also been used frequently for artifact removal. Moreover, Harmon-Jones and Peterson (2009) indicate that it is advisable to limit artifacts from muscle activity by training the subjects to limit muscle movements. However, they also stress that muscle artifacts cannot be avoided in specific situations. Specifically, they argue that this is the case in studies of emotion, a topic that holds great potential for neuroIS research (Dimoka et al., 2012; Riedl, 2013), and write that:

924

Electroencephalography (EEG) as a Research Tool in the Information Systems Discipline: Foundations, Measurement, and Applications

if an intense amount of disgust (one of the major human emotions) is evoked, the facial muscles of the participant will move and create muscle artifact in the EEG, particularly in frontal and temporal regions. Removing these muscle movements is not advisable, as emotions are occurring during these movements (Harmon-Jones & Peterson, 2009, p. 177).

However, measuring facial EMG and using it in covariance analysis may help alleviating the problem. Another procedure to address the problem is to determine the EEG frequency of interest in the facial EMG sites and test whether this covariate accounts for the EEG effects (Harmon-Jones & Peterson, 2009). However, we note that practically applying this procedure can be difficult.

In addition to muscle activity, blinks and eye movements must not be ignored in EEG research as a potential source of measurement error. Pizzagalli (2007) indicates that blinks and eye movements mainly generate activity in the delta and theta range (i.e., < 8Hz), and blinks, usually lasting between 200 and 400ms, can generate artifacts with an amplitude up to 800 μV. In many EEG studies, researchers use additional electrodes to record vertical and horizontal eye movements because this forms the basis for detecting ocular artifacts. Specifically, two electrodes are affixed below and above one eye to record vertical eye movement, and two electrodes are affixed at the extremities of an eye to record horizontal movements (Pizzagalli, 2007). Based on these data and application of specific algorithms, EOG artifacts can be removed from EEG data. Croft, Chandler, Barry, Cooper, and Clarke (2005) evaluate four EOG correction algorithms and outline their strengths and weaknesses. Harmon-Jones and Peterson (2009) argue that eye movement artifacts could also be dealt with in advance of EEG recording. Specifically, subjects could be trained to limit eye movements during EEG recording. However, while this procedure might appear useful at first glance, caution must be taken because explicit instructions to limit or control blinking in a specific way may interfere with brain mechanisms and, thereby, affect the EEG signal of interest. Finally, note that ICA is often used to remove ocular artifacts.

We have briefly discussed the importance of removing muscle and ocular artifacts in EEG research. However, filters can also be used to attenuate artifactual activity. Generally, digital high-pass and low-pass filters are applied to narrow the range of frequencies recorded and, thereby, filter out signals that are not of interest in the context of a specific study.

In IS research, most components related to emotionally and cognitive significant events are likely to have a frequency range from about 4 to 40Hz (see Table 1). Hence, one may use filter settings to attenuate frequencies falling outside this range. However, note that this general rule of thumb must not be blindly applied, and, therefore, the decision on filter settings should not be made without considering the specific research question at hand. Fabiani et al. (2007) substantiate this notion by writing: "Great care should be taken in the selection of filters. The amplitude and latency of an ERP component (as well as the general ERP waveform) can be distorted if the bandpass of the filter excludes frequencies of interest" (pp. 90-91). One suggestion is to apply high sampling frequencies and record data in a relatively wide band (e.g., 0.5 to 200Hz). Based on this procedure and with offline analyses, data can always be resampled and refiltered.

4.4 Analyzing the Data

In this section, we summarize important aspects related to analyzing EEG data. However, we note that we neither present detailed methodological and statistical discussions nor describe different software tools that can be used for data analysis; see, for example, EEGLAB (http://sccn.ucsd.edu/eeglab/) for further details.

Standard EEG analysis ranges from rather simple descriptions of signal characteristics (e.g., frequency or amplitude) to more detailed descriptions of how the signal, including variations in its characteristics, is distributed as a function of electrode location on the scalp (e.g., frontal alpha or right parietal beta) (Rippon, 2006). Once an averaged waveform (in case of ERP) has been calculated for each subject, one applies procedures from descriptive and inferential statistics, among techniques from other mathematical or statistical fields. For example, the *peak amplitude* of the ERP component of interest, defined as "the minimum or maximum voltage within a predefined time window in which that component emerges" (Bartholow & Amodio, 2009, p. 203), is almost always determined in EEG studies. Moreover, determination of the latency (synonym: *peak latency*, see below) of an ERP component, defined as the "time point at which the component reaches its peak value" (Bartholow & Amodio, 2009, p. 203), is common practice. Also, one often calculates the *average voltage* in a specific time window.

Figure 4, based on Fabiani et al. (2007, p. 91), shows a schematic representation of an ERP waveform with fundamental measures. Specifically, it shows the following types of measures: 1) peak latency (obtained by measuring the interval between stimulus onset and a positive or negative peak in the waveform), 2) base-to-peak amplitude (obtained by calculating the voltage difference between the voltage at the peak point and a baseline level, often the average pre-stimulus level), 3) peak-to-peak amplitude (obtained by calculating the voltage difference between the voltage at the peak point and the voltage at a previous peak of opposite polarity), and 4) area measure (obtained by integrating the voltage between two timepoints). Note that amplitude of the peak is usually quantified in microvolts (vertical axis in Figure 4) and latency in milliseconds (horizontal axis).

As Table 1 shows, different EEG frequency bands exist, each of which is related to specific mental states. One can extract frequency information via spectral analyses by which one can compute amplitude characteristics of the frequency domain of the EEG signal based on a method referred to as fast Fourier transform (FFT). In essence, spectral analyses assume that any oscillatory activity can be characterized by the sum of different sinusoidal waves with distinct frequencies and amplitude (Pizzagalli, 2007). In other words, one can decompose any quasi periodic infinite signal into sine waves with differing amounts of power in each frequency range (Baars & Gage, 2010). The objective of spectral analyses is to estimate the contribution of different frequencies to the measured EEG signal. Spectral estimates are usually calculated for discrete frequencies (see Table 1).
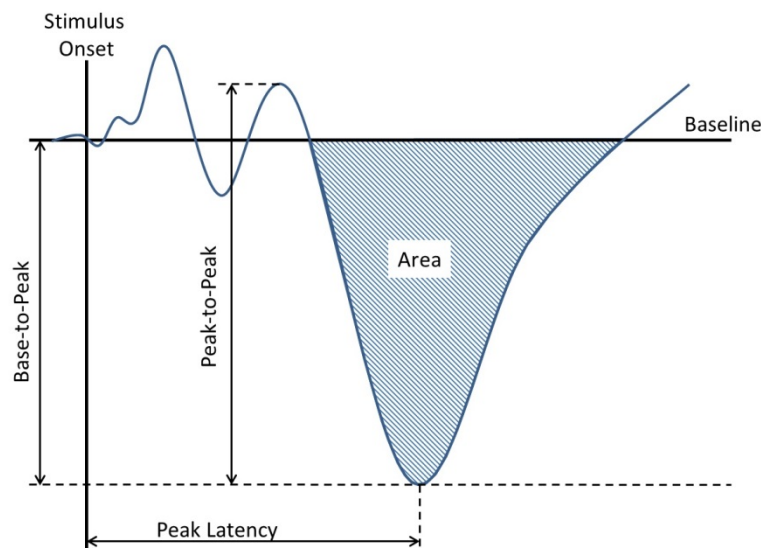

Figure 4. Fundamental Measures in EEG (ERP) Research

Spectral analyses usually involve examining the frequency composition of very short time windows (epochs) of 1 or 2 seconds, and the spectra are averaged across many time windows; note that the very short time windows are used to meet an assumption underlying FFT; namely, that of a periodic signal or one that is repeated at uniformly spaced intervals (Harmon-Jones & Peterson, 2009). Importantly, it is especially the validity of the assumption of signal uniformity that determines the efficacy of FFT. Using short epochs enables one to analyze small data segments with features that are repeated in a similar fashion at other points in the waveform. Essentially, windows are often overlapping in EEG research, which is referred to as "windowing". Generally, this approach causes the central portion of the epoch to obtain the most weight and the distal portions less weight; hence, once all time windows have been overlapped, all data points receive maximum weighting in some epochs (Harmon-Jones & Peterson, 2009). In this context, Keil et al. (2013) emphasize that, whenever researchers apply windowing procedures, they should report detailed information on relevant parameters (e.g., length of the window) in their subsequent publication(s). Moreover, they stress that such reporting is particularly relevant for procedures that aim to minimize artifacts in the beginning and end of the EEG segment to be analyzed.

With respect to spectral analyses, also note that the range for a given frequency band (e.g., beta activity, Table 1) can show considerable individual differences. Klimesch (1999), for example, provides evidence that using individually defined frequency ranges might be crucial for deriving meaningful research results. Moreover, some researchers emphasize that power data in EEG research should be transformed (e.g.,

926

Electroencephalography (EEG) as a Research Tool in the Information Systems Discipline: Foundations, Measurement, and Applications

log) before statistical analysis is performed to approximate a Gaussian distribution (Pizzagalli, 2007). Another important way to analyze EEG data is based on calculating *asymmetry metrics*. Research in cognitive neuroscience in general and in neuroIS in particular seeks to establish potential differences in activation between the two brain hemispheres. Establishing such a potential difference is important because the two hemispheres and their interactions are related to both cognitive and emotional processes. Many studies in this domain are based on Davidson's (1993) proposal that (comparatively higher) activity in regions of the left hemisphere might be related to positive affective states (facilitating approach behavior) and that (comparatively higher) activity in regions of the right hemisphere might be related to negative affective states (facilitating avoidance or withdrawal behavior) (for a review discussing evidence for and against this proposal, see Demaree, Everhart, Youngstrom, and Harrison (2005)). Evidence also shows that frontal EEG asymmetry is related to both emotional reactivity and individual differences in risk for a variety of emotion-related disorders (e.g., anxiety) (Pizzagalli, 2007). However, when researchers calculate asymmetry metrics, they should perform follow-up analyses determining the exact contribution of each hemisphere to the asymmetry index and report them in their subsequent publication(s). As an example, relatively increased right frontal activity could be the result of 1) an increase of right frontal activity, 2) a decrease of left frontal activity, or 3) a combination of both factors.

We have indicated that spectral analyses can provide information about the frequency compositions of EEG oscillations. However, it does not provide information about when in time such frequency shifts take place (Pizzagalli, 2007), which is problematic because EEG oscillations are highly dynamic, and, hence, frequency compositions may change rapidly as a result of both internal and external processes (e.g., perception of a stimulus). It follows that approaches for investigating transient changes in the frequency domain are crucial. To make such analyses possible, researchers have developed *time-frequency analyses* (e.g., wavelet analyses). Pizzagalli (2007), among others, indicates that wavelet analyses have gained in popularity in the recent past and argues that this popularity is "due to their ability to accurately resolve EEG waveforms into specific time and frequency components" (p. 67). See Samar, Bopardikar, Rao, and Swartz (1999) for a non-technical tutorial about wavelet analysis of EEG data. A traditional time frequency analysis is based on the calculation of the so-called event-related (de)synchronization (ERD/ERS) first described by Pfurtscheller and Aranibar (1977) (see also Pfurtscheller & Lopes da Silva, 1999). ERD/ERS describes the power decrease/increase in a certain frequency band relative to a reference interval—usually prior to the activity period. By calculating these ERD/ERS time courses over several bands (by applying either band power estimates or wavelet transforms), one can draw so-called ERD maps. Applying statistical tests, these colored time-frequency maps show statistically relevant changes (Graimann, Huggins, Levine, & Pfurtscheller, 2002).

Another important technique in EEG data analysis is *topographic mapping.* Here, amplitude maps are provided for different frequencies, with color-coded maps illustrating the variations in amplitude of the given frequency over the cortex at a particular point in time or period (Rippon, 2006). Moreover, it is possible to highlight areas in which statistically significant changes have occurred (in a given frequency domain and specific time window). However, Rippon (2006, p. 243) points to a problem in this context by writing:

> *Topographic maps have provided the kind of instant visibility missing from the early, chart-gazing approach, although they must be viewed with caution. The production of these maps involves an interpolation procedure whereby the values lying between the electrodes are statistically estimated in order to produce a value of best fit. These estimated values do not reflect real EEG data, however.*

Despite this limitation, however, topographic mapping plays a significant role in cognitive neuroscience research and, hence, is also of great interest to neuroIS scholars.

Most of the EEG papers in the *JMIS* and *JAIS* neuroIS special issues we mention in Section 1 use topographic maps. Figure 5 (right) shows an example of a topographic map based on Léger et al. (2014b). With respect to Figure 5 (left), the horizontal axis shows the time in milliseconds (ms), and the vertical axis shows the amplitude of the signal at electrode Pz (in µV). Léger et al. (2014b) analyzed, among other factors, cortical activity that results from perception of a pop-up email notification (stimulus onset illustrated at t0 on the horizontal axis) and did so with a focus on the interval 300-800ms after stimulus onset (see blue background color; for theoretical and methodological details, see Léger et al. 2014b). In essence, a large positive amplitude is shown (a so-called P300) that describes the participants' overall reaction to the stimulus (in this case, an attention process). Figure 5 (right) illustrates the same data in

essence in the form of a topographic map; in particular, the increased amplitude of the signal at Pz, which is illustrated in red color.
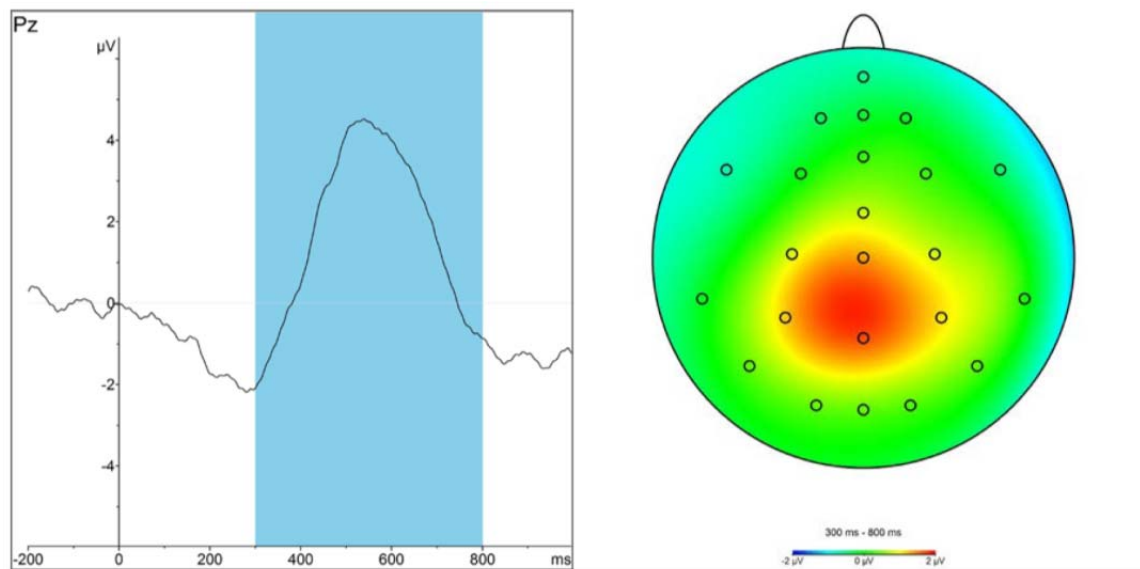

Figure 5. Example of Topographic Mapping from a NeuroIS Study (Léger et al., 2014b, p. 662)

Another increasingly important way to analyze EEG data is coherence analysis. Here, one computes correlations between electrodes placed on different locations at the scalp as a function of frequency. Rippon (2006) indicates that one takes variations in the magnitude of the correlation coefficient as a measure of the "coupling" or "uncoupling" of the respective brain regions. Thus, this type of analysis considers, at least if nonlinear versions of the technique are used, that human cognition and emotion emerge from complex interaction between different brain areas rather than from activity in one discrete brain area. Pizzagalli (2007, p. 68) confirms this view when he writes:

> In general, brain regions that are co-activated during a given cognitive process are assumed to show increased coherence ("neuronal synchronization") within specific EEG frequency bands, depending on the nature and difficulty of the task…. Such coherence measurements have been interpreted as reflecting cortical interactions or connectivity…. Consistent with this speculation, increased coherence has been generally observed with increased task complexity and efficient information processing, whereas pathological conditions characterized by dysfunctional networks (e.g., dementia, dyslexia) are characterized by decreased coherence.

Coherence values range from 0 (no correlation) to 1 (maximum correlation).

As we indicate in Section 1, EEG is not the best method to determine where in the brain activity takes place, and, hence, spatial resolution is poor when compared to several other neuroscience tools (e.g., fMRI). However, researchers can also analyze EEG data in ways that allow them to estimate the neural sources (i.e., brain regions) underlying specific latency and amplitude characteristics of the EEG signal. Specifically, one can calculate *source activity measures* (Fabiani et al., 2007). Generally, the relationship between EEG oscillations and source activity is highly difficult to describe, and this thematic domain has been discussed under the label "inverse problem" in the literature. Here, we explain that an infinite number of source configurations can generate identical surface potentials (which are measured with EEG), and, therefore, a completely unambiguous identification of the neural generators is difficult, or even impossible, to establish. Based on a discussion of papers on this research topic, Fabiani et al. (2007) propose distinguishing between algorithms for dipole (e.g., BESA) and distributed (e.g., LORETA) source analyses.

One challenge of EEG tomography is the electromagnetic inverse problem that states that one can attribute a given electrical potential, which is recorded at the scalp, to an infinite number of sources. To some degree, it is possible by making a priori assumptions about the neural sources to solve the inverse problem. The most commonly used models for EEG tomography are the weighted minimum norm and the

overdetermined dipolar models used in the well-known software packages LORETA (Pascual-Marqui, Michel, & Lehmann, 1994) and BESA (Scherg & Van Crammon, 1986)[11]. LORETA (http://www.uzh.ch/keyinst/loreta.htm) is a distributed source model assuming that extended segments of the cortex can be active simultaneously. To express local variations (and, therefore, explain variations in surface distribution), these algorithms allow the relative contribution of individual areas of the cortex to vary over timesearches for the smoothest distribution by minimizing the norm of the current vectors' Laplacian. It estimates the underlying generators without a priori assuming the number and locations of the sources. In contrast, BESA allows one to spatio-temporally model multiple current dipoles over defined intervals. While the location and orientation of the dipoles are fixed, the amplitude and polarity vary over time. In this manner, one can represent variations in surface activity in terms of variations of a few underlying brain structures' activity (Lopes da Silva & Spekreijse, 1991). Importantly, source localization precision increases non-linearly with the number of electrodes. Moreover, source localization accuracy significantly increases if one raises the number of electrodes from 30 to 64, and additional electrodes still improve the source localization results but less drastically (Baillet et al., 2001; Michel et al., 2004; Michel & Murray, 2012). EEG-based source estimation, however, offers one big advantage compared to fMRI studies: participants are not required to be in a scanner where movements are absolutely forbidden. Even better, recent research shows that, although people were moving, cortical sources could be reconstructed and analyzed with EEG-based source estimation (Seeber, Scherer, Wagner, Solis Escalante, & Müller-Putz, 2014).

Finally, covariation measures also play a role in EEG data analysis. As Fabiani et al. (2007) indicate, components may be defined with respect to segments of the ERP waveform that covary across subjects, conditions, and scalp locations in response to experimental manipulations. Thus, techniques to quantify these segments have been developed. In many studies, quantification is based on measuring the covariation of the waveform (or a particular segment of it) with an idealized wave (i.e., benchmark), which represents the component of interest.

4.5   Reporting EEG Studies

In this section, we outline how researchers should report on EEG studies in neuroIS publications. Note that the suggested guidelines must not be considered as strict rules; rather, they should be viewed as a flexible set of basic principles. Because every research study has its idiosyncrasies, strict rules are not appropriate. Yet, basic principles on how to report EEG studies in neuroIS research provide support for journal editors, reviewers, and authors. Moreover, we indicate that the basic principles are not static rules; rather, as a function of the advancements in EEG technology and corresponding discoveries along with an increasing maturity level in neuroIS research, future research will likely complement and expand on the following principles.

To develop our list of reporting guidelines, we analyzed EEG guideline papers published in other scientific fields, including psychophysiology (Keil et al., 2014; Picton, Alain, Otten, Ritter, & Achim, 2000a; Pivik et al., 1993), clinical neurophysiology (Klem, Lüders, Jasper, & Elger, 1999; Nuwer et al., 1999), and cognitive neuroscience (Handy, 2005; Jurcak, Tsuzuki, & Dan, 2007). Due to the high number of guidelines in these fields on how to report EEG studies and the enormous thematic depth with which many papers describe these guidelines, we summarize 23 important principles in Table 2 and structure them along six factors: theory, participants, instruments, experimental protocol and stimuli, data preprocessing, and data analyses.

Because the most recent EEG guideline paper that we could identify in our analyses to develop Table 2 was published recently (i.e., Keil et al., 2014), our principles consider recent discoveries in EEG research and corresponding methodology. We also considered a recent paper on a neuroIS research methodology in developing the principles (Riedl et al., 2014b). Finally, it is important to note that some of the mentioned guideline papers in psychophysiology, clinical neurophysiology, and cognitive neuroscience also provide rules on how to develop figures for high-quality EEG papers. We refer the neuroIS researcher to these publications. As an example, Keil et al. (2014) in their seminal publication specify a concrete example figure of an ERP time series plot (p. 8) and a concrete example figure of a time-frequency figure (p. 9).

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[11] With respect to the dipolar nature of EEG signal sources, we refer the reader to Delorme, Palmer, Onton, Oostenveld, and Makeig (2012).

Table 2. Basic Principles of Reporting EEG Studies in NeuroIS Research

A. Theory
1. Describe the study's theoretical foundations of the study and its corresponding research questions and/or hypotheses.
2. Discuss the contribution of using EEG in the current research context.
3. Discuss the diagnosticity of the EEG measures used in the study. Hence, one makes it explicit how precisely the measures capture the investigated theoretical construct(s) as opposed to other constructs.
B. Participants
4. Describe participants' major characteristics (e.g., age, gender, health status) and other relevant subject characteristics that are specific for the study (e.g., trust propensity in case of trust research).
5. Describe the experimental instructions that were given to the participants in detail.
6. Explicitly state that all participants gave written informed consent prior to participation in the study and that an ethics committee or an institutional review board approved the study.
C. Instruments
7. Report the EEG sensory type and its make and model.
8. Report the sensor positioning system (e.g., 10-20 system) or the exact sensor locations, including the reference and ground electrode.
9. Report the sampling rate, filters, and amplifier characteristics.
D. Experimental protocol and stimuli
10. Describe the experimental protocol in detail, including greeting, attachment of sensors, test and calibration, task instructions, experimental conditions and tasks, and removal of sensors and debriefing.
11. Report the nature of all stimuli, along with their exact timing, participant responses, and intertrial intervals.
12. Provide sample stimuli (e.g., pictures) to allow researchers to replicate the research study.
E. Data preprocessing
13. Report all preprocessing steps and their order.
14. Describe segmentation, artifact rejection, and artifact correction procedures in detail.
15. State the number of trials underlying averaging procedures.
16. Report referencing procedures and interpolation techniques (if used).
17. Report features and parameters that describe the EEG and their extraction methods (if used).
F. Data analyses
18. Report descriptive statistics.
19. Describe the statistical procedures (e.g., ANOVA, ANCOVA, t-tests) in detail and provide the inferential test statistics.
20. Specify all measurement procedures underlying data analyses, including measurement techniques (e.g., mean amplitude), time windows, and baseline periods.
21. Describe adjustment techniques for multiple comparisons and correction techniques in case of violation of model assumptions (e.g., Greenhouse-Geisser) (if used).
22. Describe methods for single-trial classification in detail (i.e., including also the kind of method to prevent from overfitting (cross-validation methods)) (if used).
23. Report all classification results by adding the actual chance level (see Müller-Putz, Scherer, Brunner, Leeb, & Pfurtscheller, 2008).

5   The Potential of EEG for IS Research

In this section, we outline the potential of EEG for IS research. To this end, we discuss research showing that several IS constructs or constructs with relevance in IS research have specific electrophysiological correlates. We base the discussion on several concrete examples.

In Section 3, we introduce the spontaneous EEG with its different frequency bands and event-related potentials (ERP). As we discuss there, both the spontaneous EEG and ERP exhibit functional significance, and, hence, specific aspects of brain oscillations are related to mental states. These mental

930

Electroencephalography (EEG) as a Research Tool in the Information Systems Discipline: Foundations, Measurement, and Applications

states, in turn, often resemble IS constructs (e.g., cognitive workload in human-computer interaction tasks) or constructs with relevance in IS research (e.g., attention). Because ERP play a more significant role in contemporary IS research than the spontaneous EEG (potential reason: ERP, in contrast to the spontaneous EEG, imply the experimental manipulation of an external stimulus, a typical procedure in mainstream IS research; see the EEG papers published in the two neuroIS special issues), we focus on ERP here. However, we start with a short, yet essential, reflection on the spontaneous EEG and its potential role in IS research. Also, we emphasize that spontaneous EEG and ERP are not better or worse than each other. Thus, one's research question determines the decision regarding whether to investigate spontaneous EEG or ERP.

5.1 Spontaneous EEG

In recent years, assessing users' mental state in the context of human-machine interaction research has become a major topic, primarily in a field referred to as neuroergonomics. Here, research investigates the effects of task difficulty, mental effort, or fatigue on changes in EEG patterns, among investigations related to other physiological indicators (e.g., skin conductance, heart rate, or blood pressure). Despite the complexity of this research domain, it appears that we can automatically detect EEG changes that result from variations in task difficulty, mental effort, or fatigue, sometimes even before the user becomes aware of a specific mental state such as fatigue. Importantly, we can see identifying excessive task difficulty, mental workload, and fatigue as a key issue for avoiding mental overload and impaired performance (Gevins & Smith, 2007). Consequently, this research domain holds great potential for IS research, particularly for human-computer interaction studies.

Using EEG in this research domain is based on the fact that the spectral composition of the ongoing EEG changes in response to human mental states. In Table 1, we summarize general knowledge about EEG frequency bands and associated mental states. While this summary might serve as a starting point for the EEG novice to develop knowledge on the functional significance of specific frequency bands, more specific research has been conducted on the ongoing EEG with relevance for the IS discipline. We present a selection of relevant findings below.

In studies investigating workload and fatigue, one can observe a change in the spectral power of the EEG signals (Gevins & Smith, 2000; Smith & Gevins, 2005). Specifically, the theta-band power (see Table 1) at the Fz electrode position (see Figure 3) increases in tasks with high mental load if compared to tasks with low mental load. In contrast, signals in the alpha-band tend to decrease at Fz and Pz positions in high-load tasks relative to low-load tasks (Gevins & Smith, 2000). Investigating fatigue-related EEG changes, Smith and Gevins (2005) report a contrary effect. Specifically, they found that cortical activation over frontal regions declined with increasing fatigue.

Methodologically, note that studies in this field often manipulate mental load using n-back-style tasks where participants are required to sustain attention to a train of stimuli. Gevins and Smith (2007, p. 17) indicate that, in these tasks, the mental load imposed on working memory varies while perceptual and motor demands are held relatively constant. As an example, in a spatial variant of the n-back task, stimuli are shown at different spatial positions on a monitor every few seconds while the participant maintains a central fixation, and participants have to compare the spatial location of each stimulus with that of a previous stimulus by indicating whether a match criterion is met by making a key press response on a keyboard or computer mouse. In low-load versions of the task, participants compare each stimulus to the first stimulus presented in each block of trials (0-back task). In higher-load versions, participants compare the position of the current stimulus with the presented one or with two or even more trials previously (1-, 2-, or n-back tasks). Obviously, this task requires one to constantly update the information stored in their working memory and to pay permanent attention to new stimuli (Gevins & Smith, 2007) and, thereby, index mental load with a particular focus on working memory.

Summarizing the results of selected studies based on the ongoing EEG, Gevins and Smith (2007) indicate that effortful attention is related to slow-wave activity in the delta band (<3Hz) and high-frequency activity in the beta (15-30Hz) and gamma (30-50Hz) band. Moreover, Holm, Lukander, Korpela, Sallinen, and Müller (2009) present an interesting study showing that the spectral power ratio of theta Fz / alpha Pz is significantly correlated with external workload (multitasking) and internal fatigue (deprivation of sleep), which suggests that using this ratio (and, therefore, ratio metrics in general) might be a useful approach for estimating cognitive overload and mental fatigue of the brain.

Also, recent neuroIS investigations have started to probe the usefulness of EEG ratio metrics in IS research. Seyedmohammadmahdi et al. (2013), for example, investigate the effect of input device (computer mouse versus touch screen) on memory retrieval and use an alpha-theta ratio measure in their investigation based on basic EEG research by Berka et al. (2007). As another example, Hariharan, Adam, and Fuong (2014) study the influence of cognitive workload on bidding behavior in electronic auctions and use an alpha-beta-theta ratio measure in their investigation based on basic research by Pope, Bogart, and Bartolome (1995). To state a third example, Fritz, Begel, Müller, Yigit-Elliott, & Züger (2014) investigate, among other things, whether one can assess task difficulty in software development accurately based on EEG, and they also use an alpha-beta-theta ratio measure in their experiment based on research by Kramer (1991) and Lee and Tan (2006). While these investigations constitute research-in-progress at the moment (i.e., they have not yet been published in peer-reviewed academic journals), it is foreseeable that EEG ratio metrics could play a significant role in future neuroIS research primarily because ratios better reflect the complex nature of many IS constructs than mere use of general frequency band information.

Another stream of electrophysiological research with significant relevance for the IS discipline concerns the relationship of the spontaneous EEG and emotion. A seminal paper in this research domain was published by Davidson (1993), who proposed that left hemisphere activity might be related to positive affective states and that right hemisphere activity might be related to negative affective states. Other studies report confirming evidence for this notion. For example, people with stable relative left frontal activity report greater positive affect to positive films, while people with stable relative right frontal activity report greater negative affect to negative films (Wheeler, Davidson, & Tomarken, 1993). Moreover, another paper indicates that greater relative left and greater relative right frontal EEG activity is associated with individual differences in dispositional positive and negative affect (Tomarken, Davidson, Wheeler, & Doss, 1992). This notion of "positive affect = left frontal" versus "negative affect = right frontal" asymmetry has been referred to as the "affective valence hypothesis" of frontal EEG asymmetry (Harmon-Jones & Peterson, 2009, p. 183).

Another important notion in the context of EEG correlates of emotion is that slower-frequency waves (delta and theta) tend to be related to affective processes (Knyazev & Slobodskaya, 2003) and faster-frequency waves (beta) tend to be related to cognitive control processes (Pfurtscheller & Lopes da Silva, 1999).

Moreover, instead of general changes in different frequency bands (see Table 1), research also indicates that one can analyze short-lasting EEG activities to derive conclusions about human mental states. Specifically, researchers have suggested using alpha spindles, short narrowband bursts in the alpha band. One can identify mental fatigue based on analyzing these alpha spindles. Simon et al. (2011) provide evidence for the effectiveness of EEG alpha spindles as an objective measure for assessing driver fatigue under real driving conditions. We argue that future neuroIS research could also use, in addition to signals in general frequency bands and corresponding ratio metrics, alpha spindles to determine user fatigue in human-computer interaction.

Another potential application of spontaneous EEG in IS research concerns the development of neuro-adaptive information systems (often based on single-trial analysis and machine learning). In a paper on application strategies for neuroscience in IS design science research, vom Brocke et al. (2013) describe engineering initiatives in which bio-signals (such as the ongoing EEG) are used as input for computer systems, which allows for real-time communication between a user and the system (see also Adam, Gimpel, Mädche, & Riedl (2014)). More specifically, Riedl (2009) and Riedl et al. (2010a), among others, have argued that brain-computer interfaces (BCI) might become relevant in non-medical organizational IS use situations[12].

In this context, Riedl and Müller-Putz, in Loos et al. (2010), indicate two long-term objectives of neuro-adaptive information systems: 1) automating process steps in administrative processes; future systems may identify the mental state of a user and start operations without an input device, or users may intentionally activate mechanical processing tasks by certain thoughts; and 2) increasing the usability of systems; for example, an automatic adaptation of the content and type of representation of information could be based on the mental state of the user (see Table 1). Moreover, they argue that achieving both

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[12] BCI have been primarily developed to sustain or restore communication of locked-in patients with the external world; such patients are people who are completely paralyzed but cognitively intact. See Birbaumer et al. (1999), Kübler et al. (2006), and Wolpaw, Birbaumer, McFarland, Pfurtscheller, and Vaughan (2002), and, for corresponding papers in the IS literature, see Moore, Storey, and Randolph (2005) and Randolph, Karmakar, and Jackson (2006).

objectives can contribute to increasing users' productivity, a major factor in using information systems in the business context (note that we explicitly stress that future research must discuss ethical issues related to this approach; see Riedl et al. (2010a, pp. 255-256) who have made a first step in this direction). However, at the moment, BCI applications in the business context are at best in their infancy, and, hence, Riedl and Müller-Putz indicate that the mentioned long-term objectives "must currently be considered as a vision rather than a reality" (Loos et al., 2010, p. 397). Further basic information on BCI is available in, for example, the following review papers and books: Allison, Dunne, Leeb, Millán, and Nijholt (2012), Millán et al. (2010), Wolpaw and Winter-Wolpaw (2012), and Wolpaw et al. (2002). Also, we emphasize that, besides standard BCI, hybrid BCI have become increasingly important during the past years. A hybrid BCI is a system which, beside the ongoing EEG, also analyzes other biosignals (e.g., electrocardiogram or electromyogram) and signals from other input devices (e.g., mouse or keyboard). System output (e.g., information presented on a screen) is based on a combination of different signals or based on selected input signals only; for details, see Müller-Putz et al. (2011) and Pfurtscheller et al. (2010).

5.2   Event-related Potential (ERP)

One can describe ERP as a waveform complex resulting from an external stimulus. An ERP typically refers to averaged EEG responses that are time-locked and phase-locked to the stimulus (Luck, 2005; Luck & Kappenman, 2012). It follows that, in ERP research, a subject is repeatedly exposed to the same experimental stimulus or stimuli if more than one is used. The ERP technique is well established in many scientific fields, such as cognitive science, ergonomics, cognitive psychology, psychophysiology, or cognitive neuroscience. ERP reflect transient, fixed latency, and fixed polarity-evoked responses (i.e., phase-locked) to a certain stimulus (i.e., time-locked). Examples of stimuli are the presentation of a word, a sound, or an image in basic research or other types of stimuli such as a user interface in more applied fields such as neuroIS. Each component in the electrophysiological signal reflects brain activation associated with one or more mental operations, and major measures in ERP research are amplitude, polarity (positive or negative), latency (in milliseconds), and scalp distribution. Therefore, one can use ERP to distinguish and identify psychological and neural sub-processes involved in complex perceptual, motor, and cognitive tasks.

ERP waves usually comprise a series of positive and negative voltage deflections related to several underlying components. Generally, components are referred to by a letter (N or P) that indicates polarity (negative or positive) and by a number that indicates either the latency in milliseconds (e.g., 100, 200, or 300) or the component's ordinal position in the waveform (e.g., 1st, 2nd, or 3rd). For example, the first substantial peaks in the waveform that often occur about 100 milliseconds after stimulus onset are called the P100 and N100 (attributes: positive or negative, 100ms latency) or the P1 and N1 (indicating that it is the first positive or negative peak). Thus, the terms "P100" and "P1" and "N100" and "N1" are used as synonyms and describe the same empirical phenomenon. The same holds true for other components (e.g., P300 or P3). Figure 6 shows the typical time course of an ERP complex; namely P1, followed by N1, P2, N2, and P3.

Besides the clinical use of ERP where ERP component abnormalities (i.e., deviations from the waveform illustrated in Figure 6) are indicators for neurological conditions such as dementia, epilepsy, multiple sclerosis, Parkinson's disease, head injuries, or stroke, they are extensively used in experimental cognitive research. In this cognitive domain, the ERP is observed as a function of tasks, stimuli (e.g., luminosity of an image or user interface, volume of sound, colors, or shapes), and timing parameters (i.e., when or how long a stimulus is presented), among other factors. Generally, the ERP waveform provides a continuous measure of human processing, which makes it possible to determine the stages (e.g., perceptual, attentional, cognitive, or motor processes) involved in executing an experimental task or perceiving a stimulus or event. Traditionally, ERP figures are plotted positive down like in Figure 6, but it is also not uncommon in the EEG research community to plot positive up. Thus, either way is correct and accepted by researchers.

Before we continue with describing five major ERP components, in this paragraph, we briefly mention some important strategies for designing EEG experiments (Luck, 2014). Generally, one can avoid many methodological issues if an experiment is well designed. In particular, it is essential that the experimental manipulation is appropriate to obtain predicted effects about the different components. Luck (2014) describes several research strategies, which we summarize here because we consider them to be highly important for neuroIS scholars; 1) focus on a single component, 2) use difference waves, 3) focus on large components, 4) use well-studied experimental manipulations.

In Sections 5.2.1 to 5.2.5, we discuss, based on concrete research examples, five major components of the ERP (P200, N200, P300, N400, and error potential) that might be particularly relevant in contemporary IS research. However, using our selection of five ERP components as a starting point, we make a call for future investigations that describe further potentially IS-relevant ERP components.
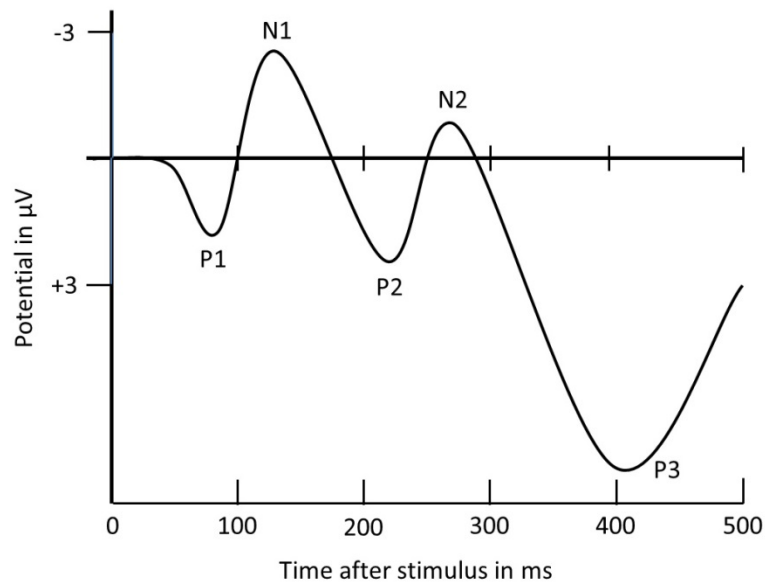
Note: ERP plotted with negative voltages upward—a common, but not universal, practice in ERP research.

Figure 6. Major Components of the ERP Waveform

Before we discuss the P200, N200, P300, N400, and the error potential, we indicate that both the P1 and N1, often referred to as early components in ERP research, have been linked primarily to attentional processes in cognitive research. Specifically, increased amplitude of the P1 and N1 reflect "increased direction of selective attention to stimulus processing" (for details and further references, see Bartholow & Amodio, 2009, p. 206). Fu and Parasuraman (2007) in a paper on ERP in neuroergonomics confirm this fact by writing that "the P1 component is a very sensitive index of the allocation of visuospatial attention" (p. 42); moreover, the same authors argue that earlier ERP components such as P1 and N1 generally have a relatively well-understood psychological meaning and involve less-complex brain mechanisms than the later ERP components (which we describe in Sections 5.2.1 to 5.2.5). In this context, Fabiani et al. (2007) indicate that these early components "are invariably elicited whenever the sensory system of interest (e.g., visual, auditory, or somatosensory) is intact … (and these early components) are thought to represent the activity of the sensory pathways that transmit the signal generated at peripheral receptors to central processing systems" (p. 98). Against this background, it becomes clear why early components of sensory evoked potentials (~ 100ms) are extensively used to diagnose neurological diseases (e.g., demyelinating diseases). Note that ERP related to sensory processes are typically referred to as evoked potential (EP), and, depending on the sensory modality under investigation, one can make further specifications, such as visual evoked potential (VEP).

5.2.1   P200

The P200 (or P2) is a component with positive polarity that peaks at about 200ms (varying between approximately 150 and 275ms) after the onset of an external stimulus. The P200 is located around the centro-frontal and the parieto-occipital region and is generally found to be maximal around the vertex (frontal region) of the scalp. The P200 represents aspects of higher-order perceptual processing modulated by attention (typically elicited as part of the normal response to visual stimuli). The P200 has been studied in various research domains, including visual search, attention, language, and memory. As such, researchers have used multiple paradigms (e.g., visual search, visual priming, or oddball

934

Electroencephalography (EEG) as a Research Tool in the Information Systems Discipline: Foundations, Measurement, and Applications

paradigms[13]) in experiments seeking to understand how manipulations of visual stimuli modulate the characteristics of the P200 (Freunberger, Klimesch, Doppelmayr, & Holler, 2007). As an example, the visual search paradigm tests perception, attention, memory, and response selection. In this paradigm, participants are instructed to focus their attention at a central point on a screen (Luck & Hillyard, 1994; Philips & Takeda, 2009). After fixation, a cue indicates the identity of a target stimulus. Participants are then instructed to identify the location of the target stimulus by pressing a button. Another paradigm (namely, visual priming) seeks to understand how prior information shapes future response. In this paradigm, participants are briefly presented with an image or word followed by a delay and a subsequent stimulus, after whose presentation the participant must make a decision. Evidence shows that target stimuli elicit larger anterior P200 components than non-targets, which suggests that top-down information processing about feature classification affects processing at the visual perception stage. Thus, the P200 may index mechanisms for selective attention, feature detection (e.g., color, orientation, or shape), and other early stages of stimulus encoding.

5.2.2 N200

The N200 (or N2) is a negative-going deflection typically evoked 180 to 325ms after the presentation of a visual or auditory stimulus. This deflection is characterized by some degree of inter-individual variation and, hence, has been interpreted with respect to psychological meaning in different ways. For instance, researchers have argued that the N200 is related to an orienting response, stimulus discrimination, and target selection. Importantly, it is also a well-established fact that detecting a deviation of a concrete stimulus from an expectation may lead to an N200. The N200 can be divided into three different sub-components: N2a (or auditory mismatch negativity, MMN), N2b, and N2c (Becker & Reinvang, 2007; Näätänen, 1995; Näätänen, Paavilainen, Titinen, Jiang, & Alho, 1993).

Researchers have hypothesized that the MMN, typically elicited in auditory oddball paradigms, reflects disparity between a deviating stimulus and a stored representation of a target stimulus. Additionally, a visual counterpart to the auditory MMN has been observed in response to changes in visual stimuli (approximately 120-200ms post-stimulus at posterior sites), referred to as vMMN (Czigler, Balazs, 2002; Pazo-Alvarez, Cadaveira, & Amenedo, 2003). Moreover, while attention is necessary to elicit an N200, the MMN does not necessarily imply attention. Based on the fact that the MMN may emerge regardless of attention to a stimulus, Picton et al. (2000b) suggest that the MMN likely represents an automatic novelty-sensing process.

In another study, researchers have found the N200 in the context of rapid emotional evaluation of advertising logos (Handy, Smilek, Geiger, Liu, & Schooler, 2008). Handy et al. (2008) investigated whether the visuocortical processing of logos can include an implicit hedonic evaluation. Specifically, they asked subjects to view unfamiliar commercial logos in the context of a target identification task, and the authors recorded physiological responses to these objects based on ERP. Afterward, subjects identified those logos that were most liked or disliked. The authors analyzed how ERP responses to logos varied as a function of hedonic evaluation. The results indicate that visuocortical processing shows an increase of the early positive component (P100) at central and parietal sites and an increase of the later negative component (N200) at parietal and occipital sites in the case of disliked logos. Generally, the results demonstrate that it is possible to use early ERP components (here, the P100 and N200) as indicators for people's hedonic preferences. It is obvious that this experiment offers application potential for neuroIS. First, IS scholars could use different versions of websites, instead of commercial logos, to replicate the findings. Second, based on Handy et al.'s study, users could be presented different versions of websites and, in the case that the perception of one version (V1) resulted in a P100 and/or N200 (at the sites described above) while another version (V2) did not, the implication would be that V1 is less liked than V2. This "ERP-based evaluation" might be used as a usability engineering method to complement more traditional methods such as interviews, questionnaires, cognitive walkthroughs, or heuristic evaluations.

5.2.3 P300

The P300 is considered to reflect information processing related to attentional and memory mechanisms. Sutton et al. (1965) first described it, and it is presumably the most widely studied ERP component in

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[13] In an oddball paradigm, presentations of sequences of repetitive stimuli (e.g., visual or auditory) are sometimes interrupted by a deviant stimulus. The participant is asked to react to deviant stimuli (e.g., by pressing a button or by counting the number of occurrences of deviant stimuli). The more common stimuli, in contrast, usually do not require a response.

cognitive research. More recent evidence has shown that the P300 comprises two subcomponents: the P3a (also referred to as "novelty P3") and the P3b (also referred to as "classical P300"). The P3a is a positive-going brain potential displaying a maximum amplitude over frontal/central electrode sites and a peak latency falling in the range of 250-280ms. This wave has been associated with engaging attention (especially the orienting, involuntary shifts to changes in the environment) and processing novelty. In contrast, the P3b is a positive-going potential peaking at around 300ms, though the peak can vary in latency from 250-500ms depending on the task. Amplitudes are typically highest on the scalp over parietal brain areas. Generally, P3b is related to likelihood of events, and the less likely an event, the larger the P3b (Katayama & Polich, 1998; Simmons, Graham, & Miles, 2001).

The P300 is also related to motivation, a fact that well established since the 1980s. One experiment by Begleiter et al. (1983) investigated ERP of two equiprobable visual stimuli (0.00 and 1.00) under three different conditions. In the baseline condition, participants attended to both stimuli and pressed the appropriate button to each stimulus. In the accuracy/incentive condition, participants earned one dollar each time the 1.00 stimulus was shown by accurately pressing the appropriate button after each stimulus (note that incorrect presses to either stimulus led to the loss of a dollar). In the speed-accuracy/incentive condition, participants only earned one dollar to the 1.00 stimulus if they accurately pressed the correct button within 350ms (note that reaction times >350ms to either stimulus resulted in the loss of a dollar). The findings of the study show that the P300 amplitude was significantly different with differential incentive values, and, because stimuli were equiprobable, the authors interpreted their findings as evidence that the P300 reflects the subjective motivational properties of a stimulus. Hömberg, Grünewald, and Grünewald-Zuberbier (1981), for example, report similar results. More recent evidence substantiates these earlier findings. Goldstein et al. (2006), for example, investigated the influence of monetary reward (0, 1, and 45 cents) on the P300. In essence, their results indicate that the P300 amplitude was significantly larger for 45 cents compared to the 1 and 0 cent conditions. Moreover, these physiological findings correspond to the monotonically positive subjective ratings of interest and excitement on the task (i.e., 45>1>0). Thus, the P300 is sensitive to relative reward value.

Motivated by the finding that the P300 may indicate reward value, researchers have questioned whether one can also use ERP to identify human design preferences in the sense of like versus dislike. If this question had been answered positively, this could have had significant influence on design initiatives in general and on user interface and website design in particular. Wriessnegger, Freislederer, & Müller-Putz (2013) conducted a pilot study based on a rapid serial visual presentation (RSVP) paradigm in this context. Specifically, they displayed "likeable" and "dislikable" objects (chairs and cars) and recorded ERP; they determined likeability based on a rating task. In essence, the mean P300 waveform showed a significant difference between the experimental conditions. Moreover, they also classified the results, which resulted in classification accuracies between 82.48 and 98.55 percent. Thus, based on ERP information, it is possible to accurately predict whether a person likes or dislikes a particular object. This pilot study is a first step toward successfully implementing a "product design BCI", which would provide a novel evaluation tool not only in arts and product design but also in design processes in general, with potential influence on usability engineering. However, note that one can use not only the P300 to assess human design preferences; rather, one can use other ERP components and EEG frequency information in general to discriminate people's like versus dislike ratings (Wriessnegger, Hackhofer, & Müller-Putz, 2015; Yilmaz, Korkmaz, Arslan, Güngör, & Asyali, 2014).

Another interesting IS application of the P300 is reported in a review paper on technostress (Riedl, 2013). Specifically, Trimmel and Huber (1998) investigated stress-related after effects of human interaction with computers via EEG. In this experiment, subjects completed three paper/pencil tasks (text editing, solving intelligence test items, and filling out a questionnaire) and three human-computer interaction tasks (text editing, executing a tutorial program or programming, and playing the video game Tetris). The duration of each task was seven minutes, and the order was randomized. After each experimental condition, ERP was recorded (electrode sites: F3, F4, Cz, P3, and P4). In essence, the study found that the P300 amplitude was smaller after the human-computer interaction tasks if compared to the paper/pencil conditions. But what does this result mean from a cognitive viewpoint? Based on analyses of related work, Trimmel and Huber argue that reduced P300 amplitudes "can be interpreted as a sign of fatigue or depletion of resources" (p. 654). It follows that this ERP study may serve as an example in which an important construct in IS research (namely, fatigue) has been conceptualized and measured physiologically (namely, based on the P300).

Boudreau et al. (2008) present another ERP study with relevance for IS research. To address the neurocognitive mechanisms that underlie choices made after receiving information from an anonymous individual, the authors recorded reaction times and event-related brain potentials as participants played the coin toss game[14]. In the study, the authors manipulated the perceived trustworthiness of the reporter (the individual who reports the outcome of a coin toss to the participant). That is, they varied 1) the interests of the reporter and the participants and 2) the institutional context in which the reporter sent the report. In the first condition, the common interests condition, the authors told participants that a correct prediction of the coin toss outcome would result in a financial benefit for both the participant and the reporter. In the second condition, the conflicting interests condition, the authors told the participants that a correct prediction of the coin toss outcome would result in a financial benefit for only the participant and that an incorrect prediction would result in a financial benefit for only the reporter. Finally, in the penalty for lying condition, conflicting interests between the reporter and the participant were maintained, but an institution was imposed on the reporter; namely, a penalty for lying.

As the behavioral results of the study show, participants in both the common interests and penalty for lying condition almost always based their predictions on the reporter's statement, while participants ignored the statement in the conflicting interests condition. Additionally, the EEG results also revealed that the P300 amplitude was larger for reports in the common interests condition than it was for the other two conditions. Based purely on the behavioral responses, participants are equally likely to trust a reporter who shared common interests with them and a reporter who was made trustworthy by an institution (namely, a penalty for lying). The fact that reports in the common interests condition elicited a larger P300 component than in the penalty for lying condition reflects evidence that participants' brains processed information differently in the common interests condition; that is, they perceived reports from the common interests reporter to be more informative than those in the penalty for lying condition (Boudreau, McCubbins, & Coulson, 2008). Considering the enormous relevance of trust for online transactions (e.g., auctions or online shopping) along with the fact that trust has been identified as a major topic in IS research (Steininger, Riedl, Roithmayr, & Mertens, 2009), the implications of the Boudreau et al. (2008) study for IS research are both evident and important. Imagine, for example, an eBay- or Amazon-like website that contained information about a product (e.g., product description text) or seller (e.g., positive or negative feedback from previous transactions in feedback profiles). Based on investigating the P300 elicited by the processing of product or seller information, IS scholars might infer the degree of informativeness of textual descriptions in online environments. In other words, one could use the P300 as a measure for informativeness to complement traditional measures such as self-reports. Considering the results of a recent review on the biology of trust (Riedl & Javor, 2012) that has shown that fMRI has been used much more frequently than EEG in trust research (revealing a significant gap in the scientific literature), we make a call for researchers to use the P300 and to apply EEG in general in IS trust research.

5.2.4   N400

The N400 is a further ERP component characterized by a negative-going deflection that peaks around 400ms after stimulus onset, typically maximal over centro-parietal electrode sites. Kutas and Hillyard (1980a) discovered the N400. They conducted an ERP experiment looking at the brain's response to unexpected words at the end of sentences. Based on previous evidence that unexpected or surprising stimuli may result in a P300, they hypothesized that such a finding could possibly be replicated in situations in which people read sentences with anomalous endings. For example, most people in Western cultures would complete the sentence "I take coffee with cream and…" with the word "sugar". Thus, ending this sentence with an anomalous word such as "dog" was hypothesized to result in a P300. However, instead of a large positive deflection, anomalous endings, when compared to sentences with expected endings, elicited a large negative deflection (specifically, a N400). Moreover, this study found that a semantically expected but physically unexpected word elicited a P300 instead of a N400 (an example for such a sentence is "She put on her high-heeled SHOES"). These findings suggest that the N400 is also related to semantic processing and not only a simple response to unexpected words (see also (Kutas & Hillyard, 1980b)). Generally, the N400 is part of the normal brain response to words and other meaningful stimuli, including signs, pictures, faces, sounds, and smells (Kutas & Federmeier, 2000, 2011). The N400 also plays an important role in categorization processing (Núñez-Peña & Honrubia-

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[14] In the coin toss game, participants guess the outcome of an unseen coin toss after they receive information from an anonymous reporter who knows the outcome of the coin toss but who is under no obligation to communicate it truthfully.

Serrano, 2005), a fact that was confirmed recently in the context of consumer psychology. Specifically, Wang, Ma, and Wang (2012) investigated ERP correlates of categorization processing in a brand-perception task. Subjects were confronted with two sequential stimuli in a pair that comprised a soft drink brand name (S1) and a product name (S2) that comprised two categories (namely, beverage (typical product: Coke-branded soda water) and clothing (atypical product: Coke-branded sportswear)). The results indicate that the N400 was more largely distributed in frontal, frontal-central, and central areas when S2 was processed. Thus, when the product was atypical for the brand, an N400 could be observed, which suggests that the N400 is related to unconscious mental categorization. Obviously, this finding could be used in IS research to find out in a relatively objective way whether a person considers a specific object as an element of a specific category or not.

5.2.5 Error Potential

The idea of the error potential (ErrP), often also referred to as error-related negativity (ERN) due to its negative polarity (see Figure 7), came up in the early 1990s. Researchers describe it as a characteristic waveform over the anterior cingulate cortex (ACC), a brain region well-known for its functional role in conflict monitoring and error processing (Botvinick, Nystrom, Fissell, Carter, & Cohen, 1999; Botvinick, Cohen, & Carter, 2004; Carter et al., 1998; Mathalon, Whitfield, & Ford, 2003). ERN develops concurrently with response onset and often peaks within 100ms after onset; however, depending on the type of error peak, latencies may also range up until 500ms after response onset. Generally, the ERN occurs after one perceives erroneous events. During the past decades, researchers have discovered different types of ErrP, such as the response ErrP (Falkenstein, Hohnsbein, Hoorman, & Blanke, 1990), the feedback ErrP (Miltner, Braun, & Coles, 1997), the observation ErrP (van Schie, Mars, Coles, & Bekkering, 2004), and the interaction ErrP (Ferrez & del R. Millán, 2005, 2008). Intriguingly, one can even observe ERN after response errors of which humans are unaware; however, the ERN is usually reduced compared to situations in which a person is aware of a response error (Nieuwenhuis, Ridderinkhof, Blom, Bang, & Kok, 2001).
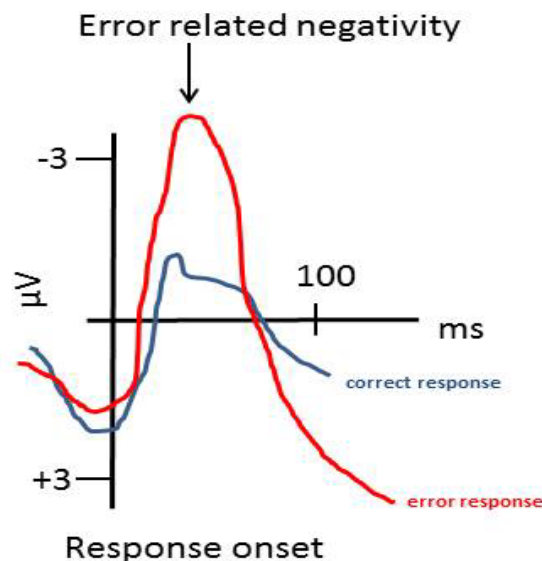

Figure 7. Error-related Negativity (ERN)

Bartholow and Amodio (2009, p. 208) report an important cognitive function related to ERN. In essence, they indicate that ERN could be a neural "distress signal" sent by the ACC to other brain regions with the goal to increase cognitive control. It follows that this signal might also increase vigilance in situations in which errors are perceived. From a motivation perspective, it is a basic human need to feel secure that one's environment is in proper order. Thus, if an error is detected people's actions tend to correct the error, and ERN is a neural mechanism that precedes those actions. A major implication of this mechanism is that IS researchers could use ERN as a relatively objective indicator to measure users' error perceptions in human-computer interaction tasks. Importantly, researchers have demonstrated that such error perceptions may pertain not only to one's own errors (e.g., wrong system input) but also to system errors (e.g., wrong system output) (Ferrez & del R. Millán, 2005, 2008).

938

Electroencephalography (EEG) as a Research Tool in the Information Systems Discipline: Foundations, Measurement, and Applications

5.3 Summary

In Section 5, we outline the potential of EEG for neuroIS research based on selected sample investigations. To this end, we discuss investigations showing that several IS constructs or constructs with relevance in IS research have specific EEG correlates. These correlates, along with others, may form the conceptual foundation of future neuroIS EEG studies. Table 3 summarizes our discussion and outlines EEG research with IS relevance based on a distinction between the spontaneous EEG and event-related potentials (ERP). Note that the research presented in Table 3 is mainly illustrative, and, hence, we make a future call for reviews that comprehensively analyze what is known about the EEG correlates of specific IS constructs (e.g., mental workload). Despite this limitation of being illustrative rather than comprehensive, the present compilation of studies might serve as a starting point for the IS novice who wants to become engaged in EEG research. Moreover, the compilation is meant to provide an impression of the diversity of constructs and topics to be studied with EEG in the IS discipline. Also, we emphasize that measurement instruments in general and, hence, also EEG must be evaluated in consideration of six factors that are critical for a neuroIS research methodology; namely, reliability, validity, sensitivity, diagnosticity, objectivity, and intrusiveness (for details, see Riedl et al. (2014b) who provide definitions for and foundations of these six factors and corresponding examples). Without reflecting on these six factors in a specific research context, it is impossible to leverage the full potential of physiological measurement in IS research. Thus, we make an explicit call that authors of EEG studies should proactively deal with these factors in their papers.

Table 3. EEG Research with Relevance for Selected IS Constructs

Construct/topic	EEG measure	Literature (selected examples)
Ongoing EEG		
Mental load	Theta band (Fz) ↑ Alpha band (Fz, Pz) ↓	Gevins & Smith (2000), Smith & Gevins (2005)
Affective processes	Slow-frequency waves (delta and theta band)	Bartholow & Amodio (2009), Knyazev & Slobodskaya (2003)
Cognitive processes	Fast-frequency waves (primarily beta)	Bartholow & Amodio (2009), Pfurtscheller & Lopes da Silva (1999)
Positive affect	Left frontal asymmetry	Davidson (1993), Tomarken et al. (1992), Wheeler et al. (1993); see also Demaree et al. (2005) who challenge this notion
Negative affect	Right frontal asymmetry	Davidson (1993), Tomarken et al. (1992), Wheeler et al. (1993); see also Demaree et al. (2005) who challenge this notion
Memory performance, cognitive workload, fatigue	Alpha-theta ratio	Berka et al. (2007), Gevins & Smith (2007), Holm et al. (2009)
Cognitive workload, task difficulty	Alpha-beta-theta ratio	Kramer (1991), Pope et al. (1995)
Fatigue	Alpha spindles	Simon et al. (2007)
Event-related potentials (ERP)		
Selective attention, state of arousal	P1	Hillyard, Vogel, & Luck (1998), Vogel & Luck (2000), Luck, Woodman, & Vogel (2000)
Spatial attention, discriminative processing	N1	Hopf, Vogel, Woodman, Heinze, & Luck (2002), Mangun (1995), Vogel & Luck (2000)
Cognitive matching, detection of target stimuli, selective attention, feature detection (e.g., color, orientation, or shape)	P200	Freunberger et al. (2007), Luck & Hillyard (1994), Philips & Takeda (2009)
Detection of a deviation of a concrete stimulus from an expectation, automatic novelty-sensing, hedonic preferences	N200	Folstein & Van Petten (2008), Handy et al. (2008), Picton et al. (2000b)

Table 3. EEG Research with Relevance for Selected IS Constructs

Attention, memory, motivation, reward value, design preferences, fatigue, informativeness	P300	Begleiter et al. (1983), Boudreau et al. (2008), Goldstein et al. (2006), Sutton, Braren, Zublin, & John (1965), Wriessnegger et al. (2013)
Semantic processing, unconscious mental categorization	N400	Kutas & Hillyard (1980a, 1080b), Núñez-Peña & Honrubia-Serrano (2005), Wang et al. (2012)
Perception of erroneous events, distress	Error-related negativity (ERN)	Bartholow & Amodio (2009), Falkenstein et al. (1990), Ferrez & del R. Millán (2005, 2008), Kreilinger, Neuper, & Müller-Putz (2012)

6   Conclusion

The concept of neuroIS has recently emerged in the IS discipline. We investigated the contemporary literature to reveal that EEG is a widely used tool. Against the background of this relevance and considering that previous descriptions of EEG in the neuroIS literature have only scantily outlined theoretical and methodological aspects related to this tool, we introduce EEG from a layman's perspective. We hope—based on the knowledge we provide in this paper—that IS researchers can make an informed decision about whether EEG could, or should, become part of their toolbox. If properly used and viewed as a complement to traditional methods (e.g., survey or clickstream analysis) and other neuroscience and psychophysiological tools (e.g., fMRI or the electrocardiogram), EEG offers great potential to advance IS research.

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References

Adam, M. T. P., Gimpel, H., Mädche, A., & Riedl, R (2014). Stress-sensitive adaptive enterprise systems: Theoretical foundations and design blueprint. In *Proceedings of the Gmunden Retreat on NeuroIS 2014* (pp. 39-41).

Allison, B. Z., Dunne, S., Leeb, R., Millán, J. R., & Nijholt, A. (Eds.). (2012). *Towards practical brain-computer interfaces: bridging the gap from research to real-world applications.* Heidelberg: Springer Verlag.

Allison, T., Wood, C. C., & McCarthy, G. (1986). The central nervous system. In M. G. H. Coles, S. W. Porges, & E. Donchin (Eds.), *Psychophysiology: Systems, processes, and applications* (pp. 5-25). New York: Guilford.

Astor, P. J., Adam, M. T. P., Jerčić, P., Schaaff, K., & Weinhardt, C. (2013). Integrating biosignals into information systems: A NeuroIS tool for improving emotion regulation. *Journal of Management Information Systems*, *30*(3), 247-278.

Baars, B. J., & Gage, N. M. (2010). *Cognition, brain, and consciousness: Introduction to cogntive neuroscience* (2nd ed.). Amsterdam: Elsevier.

Baillet, S., Mosher, J. C., & Leahy, R. M. (2001). Electromagnetic brain mapping. *IEEE Signal Processing Magazin*e, 14-30.

Bartholow, B. D., & Amodio, D. M. (2009). Using event-related brain potentials in social psychological research: A brief review and tutorial. In E. Harmon-Jones & J. S. Beer (Eds.), *Methods in social neuroscience* (pp. 198-232). New York: Guilford Press.

Becker, F., Reinvang, I. (2007). Mismatch negativity elicited by tones and speech sounds: Changed topographical distribution in aphasia. *Brain and Language*, *100*, 69-78.

Begleiter, H., Porjesz, B., Chou, C. L., & Aunon, J. I. (1983). P3 and stimulus incentive value. *Psychophysiology, 20*, 95-101.

Berger, H. (1929). Uber das Elektrenkephalogramm des Menschen. *Archiv für Psychiatrie*, *87*, 527-570.

Berka, C., Levendowski, D. J., Lumicao, M. N., Yau, A., Davis, G., Zivkovic, V. T., Olmstead, R. E., Tremoulet, P. D., & Craven, P. L. (2007). EEG correlates of task engagement and mental workload in vigilance, learning, and memory tasks. *Aviation, Space, and Environmental Medicine, 78*(5), B231-B244.

Birbaumer, N., Ghanayim, N., Hinterberger, T., Iversen, I., Kotchoubey, B., Kübler, A., Perelmouter, J., Taub, E., & Flor, H. (1999). A spelling device for the paralysed. *Nature, 398*(6725), 297-298.

Boudreau, C., McCubbins, M. D., & Coulson, S. (2008). Knowing when to trust others: An ERP study of decision making after receiving information from unknown people. *Social Cognitive and Affective Neuroscience*, *4*, 23-34.

Botvinick, M. M., Cohen, J. D., & Carter, C. S. (2004). Conflict monitoring and anterior cingulate cortex: An update. *Trends in Cognitive Sciences, 8*(12), 539-546.

Botvinick, M. M., Nystrom, L. E., Fissell, K., Carter, C. S., & Cohen, J. D. (1999). Conflict monitoring versus selection-for-action in anterior cingulate cortex. *Nature, 402*(6758), 179-181.

Buzsaki, G., & Draguhn, A. (2004). Neuronal oscillations in cortical networks. *Science*, *304*(5679), 1926-1929.

Cacioppo, J. T., Petty, R. E., & Marshall-Goodell, B. (1985). Physical, social, and inferential elements of psychophysiological measurement. In P. Karoly (Ed.), *Measurement strategies in health psychology* (pp. 263-300). New York: John Wiley & Sons.

Cahn, B. R., & Polich, J. (2006). Meditation states and traits: EEG, ERP, and neuroimaging studies. *Psychological Bulletin*, *132*(2), 180-211.

Carter, C. S., Braver, T. S., Barch, D. M., Motvinick, M. M., Noll, D., & Cohen, J. D. (1998). Anterior cingulate cortex, error detection, and the online monitoring of performance. *Science*, *280*(5364), 747-749.

Croft, R. J., Chandler, J. S., Barry, R. J., Cooper, N. R., & Clarke, A. R. (2005). EOG correction: A comparison of four methods. *Psychophysiology*, *42*, 16-24.

Crone, N., Sinai, A., Korzeniewska, A. (2006). High-frequency gamma oscillations and human brain mapping with electrocorticography. *Progress in Brain Research*, *159*, 275-295.

Czigler, I., Balazs, L., & Winkler, I. (2002). Memory-based detection of task-irrelevant visual changes. *Psychophysiology*, *39*, 869-873.

Davidson, R. J. (1993). Cerebral asymmetry and emotion: Conceptual and Methodological conundrums. *Cognition and Emotion*, *7*(1), 115-138.

Davidson, R. J., Jackson, D. C., & Larson, C. L. (2000). Human Electroencephalography. In J. T. Cacioppo, L. G. Tassinary, & G. G. Bernston (Eds.), *Handbook of psychophysiology* (2nd ed., pp. 27-56). Cambridge: Cambridge University Press.

Delorme, A., Palmer, J., Onton, J., Oostenveld, R., & Makeig, S. (2012). Independent EEG sources are dipolar. *PLoS ONE*, *7*(2), 1-14.

Demaree, H. A., Everhart, D. E., Youngstrom, E. A., & Harrison, D. W. (2005). Brain lateralization of emotional processing: Historical roots and a future incorporating "dominance". *Behavioral and Cognitive Neuroscience Reviews*, *4*(1), 3-20.

Dimoka, A. (2010). What does the brain tell us about trust and distrust? Evidence from a functional neuroimaging study. *MIS Quarterly*, *34*(2), 373-396.

Dimoka, A., Pavlou, P. A., & Davis, F. D. (2007). NeuroIS: The potential of cognitive neuroscience for information systems research. In *Proceedings of the 28th International Conference on Information Systems* (pp. 1-20).

Dimoka, A., Banker, R. D., Benbasat, I., Davis, F. D., Dennis, A. R., Gefen, D., Gupta, A., Ischebeck, A., Kenning, P., Müller-Putz, G., Pavlou, P. A., Riedl, R., vom Brocke, J., & Weber, B. (2012). On the use of neurophysiological tools in IS research: Developing a research agenda for NeuroIS. *MIS Quarterly*, *36*(3), 679-702.

Fabiani, M., Gratton, G., & Federmeier, K. D. (2007). Event-related brain potentials: Methods, theory, and applications. In J. T. Cacioppo, L. G. Tassinary, & G. G. Berntson (Eds.), *Handbook of psychophysiology* (3rd ed.) (pp. 85-119). Cambridge: Cambridge University Press.

Falkenstein, M., Hohnsbein, J., Hoormann, J., Blanke L. (1990). Effects of errors in choice reaction tasks on the ERP under focused and divided attention. In C. H. M. Brunia, A. W. K. Gaillard, & A. Kok (Eds.), *Psychophysiological brain research* (pp. 192-195). Tilburg, The Netherlands: Tilburg University Press.

Ferrez, P. W., & del R. Millán, J. (2005). You are wrong! Automatic detection of interaction errors from brainwaves. In *Proceedings of the 19th International Joint Conference on Artificial Intelligence* (pp. 1413-1418).

Ferrez, P. W., & del R. Millán, J. (2008). Error-related EEG potentials generated during simulated brain-computer interaction. *IEEE Transactions on Bio-Medical Engineering*, *55*(3), 923–929.

Folstein, J. R., Van Petten, C. (2008). Influence of cognitive control and mismatch on the N2 component of the ERP: A review. *Psychophysiology*, *45*, 152-170.

Freunberger, R., Klimesch, W., Doppelmayr, M., Holler, Y. (2007). Visual P2 component is related to theta phase-locking. *Neuroscience Letters*, *426*, 181-186.

Fritz, T., Begel, A., Müller, S. C., Yigit-Elliott, S., & Züger, M. (2014). Using psycho-physiological measures to assess task difficulty in software development. In *Proceedings of the 36th International Conference on Software Engineering.*

Fu, S., & Parasuraman, R. (2007). Event-related potentials (ERPs) in neuroergonomics. In R. Parasuraman & M Rizzo (Eds.), *Neuroergonomics: The brain at work* (pp. 32-50). Oxford: Oxford University Press.

Gasser, T., & Molinari, L. (1996). The analysis of the EEG. *Statistical Methods in Medical Research*, *5*, 67-99.

Gevins, A., & Smith, M. E. (2000). Neurophysiological measures of working memory and individual differences in cognitive ability and cognitive style. *Cerebral Cortex*, *10* (9), 829-839.

Gevins, A., & Smith, M. E. (2007). Electroencephalography (EEG) in neuroergonomics. In R. Parasuraman & M Rizzo (Eds.), *Neuroergonomics: The brain at work* (pp. 15-31). Oxford: Oxford University Press.

Goldstein, R. Z., Cottone, L. A., Jia, Z., Maloney, T., Volkow, N. D., & Squires, N. K. (2006). The effect of graded monetary reward on cognitive event-related potentials and behavior in young healthy adults. *International Journal of Psychophysiology*, *62*(2), 272-279.

Graimann, B., Huggins, J. E., Levine, S. P., & Pfurtscheller, G. (2002). Visualization of significant ERD/ERS patterns in multichannel EEG and ECoG data. *Clinical Neurophysiology*, *113*, 43-47.

Gratton, G. (2007). Biosignal processing. In J. T. Cacioppo, L. G. Tassinary, & G. G. Berntson (Eds.), *Handbook of psychophysiology* (3rd ed., pp. 834-858). Cambridge: Cambridge University Press.

Handy, T. (2005). *Event-related potentials: A methods handbook.* Cambridge, MA: MIT Press.

Handy, T. C., Smilek, D., Geiger, L., Liu, C., & Schooler, J. W. (2008). ERP evidence for rapid hedonic evaluation of logos. *Journal of Cognitive Neuroscience*, *22*(1), 124–138.

Hariharan, A., Adam, M. T., & Fuong, K. (2014). Towards understanding the interplay of cognitive demand and arousal in auction bidding. In *Proceedings of the European Conference on Information Systems.*

Harmon-Jones, E., & Peterson, C. K. (2009). Electroencephalographic methods in social and personality psychology. In E. Harmon-Jones & J. S. Beer (Eds.), *Methods in social neuroscience* (pp. 170-197). New York: Guilford Press.

Hjorth, B. (1975). An on-line transformation of EEG scalp potentials into orthogonal source derivations. *Clinical EEG and Neuroscience*, *39*, 526-530.

Hillyard, S. A., Vogel, E. K., & Luck, S .J. (1998). Sensory gain control (amplification) as a mechanism of selective attention: Electrophysiological and neuroimaging evidence. *Philosophical Transactions of the Royal Society: Biological Sciences*, *353*, 1257-1270.

Hobson, J., & Pace-Schott, E. (2002). The cognitive neuroscience of sleep: Neuronal systems, consciousness and learning. *Nature Reviews Neuroscience*, *3*(9), 679-693.

Holm, A., Lukander, K., Korpela, J., Sallinen, M., & Müller, K. M. (2009). Estimating brain load from the EEG. *Scientific World Journal*, *9*, 639-651.

Hopf, J.-M., Vogel, E. K., Woodman, G. F., Heinze, H.-J., & Luck, S. J. (2002). Localizing visual discrimination processes in time and space. *Journal of Neurophysiology*, *88*, 2088-2095.

Hömberg, V., Grünewald, G., & Grünewald-Zuberbier, E. (1981). The variation of amplitude in a money-winning paradigm in children. *Psychophysiology*, *18*(3), 258-262.

Hughes, J. R. (2008). Gamma, fast, and ultrafast waves of the brain: their relationships with epilepsy and behavior. *Epilepsy & Behavior, 13*(1), 25-31.

Jacobs, J., & Kahana, M.J. (2010). Direct brain recordings fuel advances in cognitive electrophysiology. *Trends in Cognitive Sciences*, *14*, 162-171.

Jasper, H. H. (1958). The ten-twenty electrode system of the International Federation. *Electroencephalography & Clinical Neurophysiology, 10*, 371-375.

Jurcak, V., Tsuzuki, D., & Dan, I. (2007). 10/20, 10/10, and 10/5 systems revisited: Their validity as relative head-surface-based positioning systems. *NeuroImage*, *34*(4), 1600-1611.

Katayama, J., & Polich, J. (1998). Stimulus context determines P3a and P3b. *Psychophysiology*, *35*, 23-33.

Keil, A., Debener, S., Gratton, G., Junghöfer, M., Kappenman, E. S., Luck, S. J., Luu, P., Miller, G. A., & Yee, C. M. (2014). Publication guidelines and recommendations for studies using electroencephalography and magnetoencephalography. *Psychophysiology*, *51*(1), 1-21.

Klimesch, W. (1999). EEG alpha and theta oscillations reflect cognitive and memory performance: A review and analysis. *Brain Research Reviews*, *29*, 169-195.

Klem, G. H., Lüders, H. O., Jasper, H. H., & Elger, C. (1999). The ten-twenty electrode system of the International Federation. The International Federation of Clinical Neurophysiology. *Electroencephalography & Clinical Neurophysiology*, *52, 3-6.*

Knyazev, G. G., & Slobodskaya, H. R. (2003). Personality trait of behavioral inhibition is associated with oscillatory systems reciprocal relationships. *International Journal of Psychophysiology*, *48*, 247-261.

Kramer, A. F. (1990). *Physiological metrics of mental workload: A review of recent progress.* San Diego, CA: Navy Personnel Research and Development Center.

Kreilinger, A., Neuper, C., & Müller-Putz, G. (2012). Error potential detection during continuous movement of an artificial arm controlled by brain–computer interface. *Medical & Biological Engineering & Computing*, *50*(3), 223-230.

Kübler, A., Kotchoubey, B., Kaiser, J., Wolpaw, J. R., & Birbaumer, N. (2001). Brain-computer communication: unlocking the locked-in. *Psychological Bulletin*, *127*, 358-375.

Kutas, M., & Hillyard, S. A. (1980a). Reading senseless sentences: Brain potentials reflect semantic incongruity. Science, 207, 203-208.

Kutas, M., & Hillyard, S. A. (1980b). Reading between the lines: Event-related brain potentials during natural sentence processing. *Brain and Language*, *11*(2), 354–373.

Kutas, M., Federmeier, K. D. (2000). Electrophysiology reveals semantic memory use in language comprehension. Trends in Cognitive Science, 4 (12), 463-470.

Kutas, M., & Federmeier, K. D. (2011). Thirty years and counting: Finding meaning in the N400 component of the event related brain potential (ERP). *Annual Review of Psychology*, *62*, 621-647.

Lachaux, J. P., Rudrauf, D., & Kahane, P. (2003). Intracranial EEG and human brain mapping. *Journal of Physiology Paris*, *97*, 613-628.

Lantz, G., Grave de Peralta, R., Spinelli, L., Seeck, M., & Michel, C. M. (2003). Epileptic source localization with high density EEG: how many electrodes are needed? *Clinical Neurophysiology*, *114*, 63-69.

Lee, J. C., & Tan, D. S. (2006). Using a low-cost electroencephalograph for task classification in HCI research. In *Proceedings of the 19th Annual ACM Symposium on User Interface Software and Technology* (pp. 81-90). New York: ACM.

Léger, P.-M., Riedl, R., & vom Brocke, J. (2014a). Emotions and ERP information sourcing: The moderating role of expertise. *Industrial Management & Data Systems*, *114*(3), 456-471.

Léger, P.-M., Sénecal, S., Courtemanche, F., Ortiz de Guinea, A., Titah, R., Fredette, M., & Labonte-Lemoine, È. (2014b). Precision is in the eye of the beholder: Application of eye fixation-related potentials to information systems research. *Journal of the Association for Information Systems*, *15*(10), 651-678.

Liu, A. K., Dale, A. M., & Belliveau, J. W. (2002). Monte Carlo simulation studies of EEG and MEG localization accuracy. *Human Brain Mapping, 16*(1), 47-62.

Loos, P., Riedl, R., Müller-Putz, G. R., vom Brocke, J., Davis, F. D., Banker, R. D., & Léger, P.-M. (2010). NeuroIS: Neuroscientific approaches in the investigation and development of information systems. *Business & Information Systems Engineering*, *2*(6), 395-401.

Lopes da Silva, F. H. & Spekreijse, H. (1991). Localization of brain sources of visually evoked responses using single and multiple dipoles. An overview of different approaches. In C. H. M. Brunia, G. Mulder, & M. N. Verbaten (Eds.), Event-related brain potential research (pp. 38-46). Elsevier: Amsterdam.

Lorente de Nò, R. (1947). Action potential of the motoneurons of the hypoglossus nucleus. *Journal of Cellular and Comparative Physiology*, *29*, 207-287.

Luck, S. (2005). *An introduction to the event-related potential technique.* Cambridge, MA: MIT Press.

Luck, S. (2014). *An introduction to the event-related potential technique.* Cambridge, MA: MIT Press.

Luck, S. J., & Hillyard, S. A. (1994). Electrophysiological correlates of feature analysis during visual search. *Psychophysiology*, *31*, 291-308.

Luck, S. J., & Kappenman, E. S. (Eds.). (2012). *The Oxford handbook of event-related potential components* (pp. 654-664). New York, NY: Oxford University Press.

Luck, S. J., Woodman, G. F., & Vogel, E. K. (2000). Event-related potential studies of attention. *Trends in Cognitive Sciences*, *4*, 432-440.

Makeig, S., Westerfield, M., Jung, T. P., Enghoff, S., Townsend, J., Courchesne, E., & Sejnowski, T. J. (2002). Dynamic brain sources of visual evoked responses. *Science*, *295*(5555), 690-694.

Mangun, G. R. (1995). Neural mechanisms of visual selective attention. *Psychophysiology*, *32*, 4-18.

Mathalon, D. H., Whitfield S. L., & Ford J. M. (2003). Anatomy of an error: ERP and fMRI. *Biological Psychology*, *64*(1-2), 119-141.

Michel, C. M., Murray, M. M., Lantz, G., Gonzalez, S., Spinelli, L., & Grave de Peralta, R. (2004). EEG source imaging. *Clinical Neurophysiology*, *115*(10), 2195-2222.

Michel, C. M., & Murray, M. M. (2012). Towards the utilization of EEG as a brain imaging tool. *Neuroimage*, *61*(2), 371-385.

Millán, J. D., Rupp, R., Müller-Putz, G. R., Murray-Smith, R., Giugliemma, C., Tangermann, M., Vidaurre, C., Cincotti, F., Kübler, A., Leeb, R., Neuper, C., Müller, K. R., & Mattia, D. (2010). Combining brain-computer interfaces and assistive technologies: State-of-the-art and challenges. *Frontiers in Neuroscience*, *4*, 161.

Miller, K. J., denNijs, M., Shenoy, P., Miller, J. W., Rao, R. P., & Ojemann, J. G. (2007). Real-time functional brain mapping using electrocorticography. *Neuroimage*, *37*, 504-507.

Miltner, W. H. R., Braun, C. H., & Coles, M. G. H. (1997). Event-related brain potentials following incorrect feedback in a time-estimation task: Evidence for a "generic" neural system for error-detection. *Journal of Cognitive Neuroscience*, *9*, 788–798.

Minas, R. K., Potter, R. F., Dennis, A. R., Bartelt, V., & Bae, S. (2014). Putting on the thinking cap: Using NeuroIS to understand information processing biases in virtual teams. *Journal of Management Information Systems*, *30*(4), 49-82.

Moore, M. M., Storey, V. C., & Randolph, A. B. (2005). User profiles for facilitating conversations with locked-in users. In *Proceedings of the International Conference on Information Systems* (pp. 923-936).

Müller-Putz, G. R., Breitwieser, C., Cincotti, F., Leeb, R., Schreuder, M., Leotta, F., Tavella, M., Bianchi, L., Kreilinger, A., Ramsay, A., Rohm, M., Sagebaum, M., Tonin, L., Neuper, C., & Millán, J. R. (2011). Tools for brain-computer interaction: A general concept for a hybrid BCI. *Frontiers in Neuroinformatics*, *5*(30), 1-10.

Müller-Putz, G. R., Scherer, R., Pfurtscheller, G., & Rupp, R. (2005). EEG-based neuroprosthesis control: A step towards clinical practice. *Neuroscience Letters*, *382*, 169-174.

Müller-Putz, G. R., Scherer, R., Brunner, C., Leeb, R., & Pfurtscheller, G. (2008). Better than random? A closer look on BCI results. *International Journal of Bioelectromagnetism, 10*(1), 52-55.

Näätänen, R. (1995). The mismatch negativity: a powerful tool for cognitive neuroscience. *Ear and Hearing*, *16*(1), 6-18.

Näätänen, R., Paavilainen, P., Titinen, H., Jiang, D., & Alho, K. (1993). Attention and mismatch negativity. *Psychophysiology*, *30*(5), 436-450.

Niedermeyer, E (1997). Alpha rhythms as physiological and abnormal phenomena*. International Journal of Psychophysiology*, *26*(1-3), 31-49.

Nieuwenhuis, S., Ridderinkhof, K. R., Blom, J., Band, G. P., & Kok, A. (2001). Error-related brain potentials are differentially related to awareness of response errors: Evidence from an antisaccade task*. Psychophysiology*, *38*(5), 752-760.

Núñez-Peña, M. I., & Honrubia-Serrano, M. L. (2005). N400 and category exemplar associative strength. *International Journal of Psychophysiology*, *56*, 45-54.

Nuwer, M. R., Lehmann, D., Lopes da Silva, F., Matsuoka, S., Sutherling, W., & Vibert, J. F. (1999). IFCN guidelines for topographic and frequency analysis of EEGs and EPs. The International Federation of Clinical Neurophysiology. *Electroencephalography & Clinical Neurophysiology*, *52,* 15-20.

Okada Y. (1993). Empirical bases for constraints in current-imaging algorithms. *Brain Topography, 5*(4), 373-377.

Oostenveld, R., & Praamstra, P. (2001). The five percent electrode system for high-resolution EEG and ERP measurements. *Clinical Neurophysiology*, *112*, 713-719.

Ortiz de Guinea, A., & Webster, J. (2013). An investigation of information systems use patterns: Technological events as triggers, the effects of time, and consequences for performance. *MIS Quarterly*, *37*(4), 1165-1188.

Pascual-Marqui, R. D., Michel, C. M., & Lehmann, D. (1994). Low resolution electromagnetic tomography: a new method for localizing electrical activity in the brain. *International Journal of Psychophysiology*, *18*(1), 49-65.

Pazo-Alvarez, P., Cadaveira, F., & Amenedo, E. (2003). MMN in the visual modality: A review. *Biological Psychology*, *63*, 199-236.

Pfurtscheller, G., Allison, B. Z., Brunner, C., Bauernfeind, G., Solis-Escalante, T., Scherer, R., Zander, T. O., Müller-Putz, G. R., Neuper, C., & Birbaumer, N. (2010). The hybrid BCI. *Frontiers in Neuroscience*, *4*, 42.

Pfurtscheller, G., & Aranibar, A. (1977). Event-related cortical desynchronization detected by power measurements of scalp EEG. *Electroencephalography and Clinical Neurophysiology*, *42*, 817-826.

Pfurtscheller, G., & Lopes da Silva, F. H. (1999). Event-related EEG/MEG synchronization and desynchronization: Basic principles. *Clinical Neurophysiology*, *110*, 1842-1857.

Pfurtscheller, G., Stancak, A., Jr., & Neuper, C. (1996). Event-related synchronization (ERS) in the alpha band—an electrophysiological correlate of cortical idling: A review. *International Journal of Psychophysiology*, *24,* 39-46.

Phillips, S., & Takeda, Y. (2009). An EEG/ERP study of efficient versus inefficient visual search. In N. A. Taatgen & H. van Rijin (Eds.), *Proceedings of the 31st Annual Conference of the Cognitive Science Society* (pp. 383-388).

Picton, T. W., Alain, C., Otten, L., Ritter, W., & Achim, A. (2000b). Mismatch negativity: Different water in the same river. *Audiology & Neuro Otology*, *5*, 111-139.

Picton, T. W., Bentin, S., Berg, P., Donchin, E., Hillyard, S. A., Johnson Jr., R., Miller, G. A., Ritter, W., Ruchkin, D. S., Rugg, M. D., & Taylor, M. J. (2000a): Guidelines for using human event-related potentials to study cognition: Recording standards and publication criteria. *Psychophysiology*, *37*(2), 127-152.

Pivik, R. T., Broughton, R. J., Coppola, R., Davidson, R. J., Fox, N., & Nuwer, M. R. (1993). Guidelines for the recording and quantitative analysis of electroencephalographic activity in research contexts. *Psychophysiology*, *30*(6), 547-548.

Pizzagalli, D. A. (2007). Electroencephalography and high-density electrophysiological source localization. In J. T. Cacioppo, L. G. Tassinary, & G. G. Berntson (Eds.), *Handbook of psychophysiology* (3rd ed.) (pp. 56-84). Cambridge: Cambridge University Press.

Pope, A. T., Bogart, E. H., & Bartolome, D. S. (1995). Biocybernetic system evaluates indices of operator engagement in automated task. *Biological Psychology*, *40*(1-2), 187-195.

Ramsoy, T. Z., Balslev, D. & Paulson, O. B. (2010). Methods for observing the living brain. In B. J. Baars & Gage, N. M. (Eds.), *Cognition, brain, and consciousness: Introduction to cognitive neuroscience* (2nd ed.). Amsterdam: Elsevier.

Randolph, A. B., Karmakar, S., & Jackson, M. M. (2006). Toward predicting control of a brain-computer interface. In *Proceedings of the International Conference on Information Systems* (pp. 803−812).

946

Electroencephalography (EEG) as a Research Tool in the Information Systems Discipline: Foundations, Measurement, and Applications

Regan, D. (1989). *Human brain electrophysiology: evoked potentials and evoked magnetic fields in science and medicine*. New York: Elsevier.

Riedl, R. (2009). Zum Erkenntnispotenzial der kognitiven Neurowissenschaften für die Wirtschaftsinformatik: Überlegungen anhand exemplarischer Anwendungen. *NeuroPsychoEconomics*, *4*(1), 32-44.

Riedl, R. (2013). On the biology of technostress: Literature review and research agenda. *DATA BASE for Advances in Information Systems*, *44*(1), 18-55.

Riedl, R., Banker, R. D., Benbasat, I., Davis, F. D., Dennis, A. R., Dimoka, A., Gefen, D., Gupta, A., Ischebeck, A., Kenning, P., Müller-Putz, G., Pavlou, P. A., Straub, D. W., vom Brocke, J., & Weber, B. (2010a). On the foundations of NeuroIS: Reflections on the Gmunden Retreat 2009. *Communications of the Association for Information Systems*, *27*, 243-264.

Riedl, R., Hubert, M., & Kenning, P. (2010b). Are there neural gender differences in online trust? An fMRI study on the perceived trustworthiness of eBay offers. *MIS Quarterly*, *34*(2), 397-428.

Riedl, R., & Javor, A. (2012). The biology of trust: Integrating evidence from genetics, endocrinology, and functional brain imaging. *Journal of Neuroscience, Psychology, and Economics*, *5*(2), 63-91.

Riedl, R., & Léger, P.-M. (Forthcoming). *Fundamentals of NeuroIS: Information systems and the brain*. Berlin: Springer.

Riedl, R., Kindermann, H., Auinger, A., & Javor, A. (2012). Technostress from a neurobiological perspective: System breakdown increases the stress hormone cortisol in computer users. *Business & Information Systems Engineering*, *4*(2), 61-69.

Riedl, R., Kindermann, H., Auinger, A., & Javor, A. (2013). Computer breakdown as a stress factor during task completion under time pressure: Identifying gender differences based on skin conductance. *Advances in Human-Computer Interaction.*

Riedl, R., Mohr, P., Kenning, P., Davis, F., & Heekeren, H. (2014a). Trusting humans and avatars: A brain imaging study based on evolution theory. *Journal of Management Information Systems*, *30*(4), 83-113.

Riedl, R., Davis, F. D., & Hevner, A. R. (2014b). Towards a NeuroIS research methodology: Intensifying the discussion on methods, tools, and measurement. *Journal of the Association for Information Systems*, *15*(10), i-xxxv.

Rippon, G. (2006). Electroencephalography. In C. Senior, T. Russel, & M. Gazzaniga (Eds.), *Methods in mind* (pp. 237-262). Cambridge: MIT Press.

Samar, V. J., Bopardikar, A., Rao, R., & Swartz, K. (1999). Wavelet analysis of neuroelectric waveforms: A conceptual tutorial. *Brain and Language*, *66*(1), 7-60.

Scherg, M., & Von Cramon, D. (1986). Evoked dipole source potentials of the human auditory cortex. *Electroencephalography & Clinical Neurophysiology*, *65*(5), 344-60.

Schomer, L., & Lopes de Silva, F. (Eds.). (2011). Niedermeyer's electroencephalography: Basic principles, clinical applications, and related fields (6th ed.). Philadelphia: Lippincott Williams & Wilkins.

Seeber, M., Scherer, R., Wagner, J., Solis Escalante, T., & Müller-Putz, G. (2014). EEG beta suppression and low gamma modulation are different elements of human upright walking. *Frontiers in Human Neuroscience*, *8*(485).

Seyedmohammadmahdi, M., Pierre-Majorique, L., Sylvain, S., Fredette, M., Cameron, A. F., & Riedl, R. (2013). Investigating the effect of input device on memory retrieval: Evidence from theta and alpha band oscillations. In *Proceedings of the Special Interest Group on Human-Computer Interaction*.

Simon, M., Schmidt, E. A., Kincses, W. E., Fritzsche, M., Bruns, A., Aufmuth, C., Bogdan, M., Rosenstiel, W., & Schrauf, M. (2011). EEG alpha spindle measures as indicators of driver fatigue under real traffic conditions. *Clinical Neurophysiology, 122*(6), 1168-1178.

Simmons, R. F., Graham, F. K., & Miles, M. A. (2001). On the relationship of the P3a and the novelty P3. *Biological Psychology*, *56*, 207-218.

Speckmann, E., Elger, C. E., & Altrup, U. (1993). Neurophysiologic basis of the EEG. In E. Wyllie (Ed.), *The treatment of epilepsy: Principles and practices* (pp. 185-201). Philadelphia: Lea & Febiger.

Smith, M. E., & Gevins, A. (2005). Neurophysiologic monitoring of mental workload and fatigue during operation of a flight simulator. In J. A. Caldwell & N. J. Wesensten (Eds.), Proceedings of SPIE Defense and Security Symposium, Biomonitoring for Physiological and Cognitive Performance during Military Operations (pp. 116-126). Orlando: SPIE.

Steininger, K., Riedl, R., Roithmayr, F., and Mertens, P. (2009). Fads and trends in business and information systems engineering and information systems research: A comparative literature analysis. *Business & Information Systems Engineering, 1*(6), 411-428.

Sutton, S., Braren, M., Zublin, J., & John, E. (1965). Evoked potential correlates of stimulus uncertainty. *Science*, *150*, 1187-1188.

Tams, S., Hill, K., Ortiz de Guinea, A., Thatcher, J., & Grover, V. (2014). NeuroIS—alternative or complement to existing methods? Illustrating the holistic effects of neuroscience and self-reported data in the context of technostress research. *Journal of the Association for Information Systems*, *15*(10), 723-753.

Tomarken, A. J., Davidson, R. J., Wheeler, R. E., & Doss, R. C. (1992). Individual differences in anterior brain asymmetry and fundamental dimensions of emotion. *Journal of Personality and Social Psychology, 62*, 676-687.

Trimmel, M., & Huber, R. (1998). After-effects of human-computer interaction indicated by P300 of the event-related brain potential. *Ergonomics*, *41*(5), 649-655.

van Schie, H. T., Mars, R. B., Coles, M. G. H., & Bekkering, H. (2004). Modulation of activity in medial frontal and motor cortices during error observation. *Nature Neuroscience*, *7*, 549-554.

Vogel, E. K., & Luck, S. J. (2000). The visual N1 component as an index of a discrimination process. *Psychophysiology*, *37*, 190-203.

vom Brocke, J., Riedl, R., & Léger, P.-M. (2013). Application strategies for neuroscience in information systems design science research. *Journal of Computer Information Systems*, *53*(3), 1-13.

Wang, X., Ma, Q., & Wang, C. (2012). N400 as an index of uncontrolled categorization processing in brand extension. *Neuroscience Letters*, *525,* 76-81.

Wheeler, R. E., Davidson, R. J., & Tomarken, A. J. (1993). Frontal brain asymmetry and emotional reactivity: A biological substrate of affective style. *Psychophysiology*, *30*, 82-89.

Wolpaw, J. R, Birbaumer, N., McFarland, D. J., Pfurtscheller, G., & Vaughan, T. M. (2002). Brain-computer interfaces for communication and control. *Clinical Neurophysiology*, *113*, 767-791.

Wolpaw, J. R., & Winter-Wolpaw, E. (Eds.). (2012). *Brain-computer interfaces: Principles and practice.* New York, NY: Oxford University Press.

Wolters, C. H., Grasedyck, L., & Hackbusch, W. (2004). Efficient computation of lead field bases and influence matrix for the FEM-based EEG and MEG inverse problem. *Inverse Problems, 20*(4), 1099-1116.

Wriessnegger, S. C., Freislederer, P., & Müller-Putz, G. R. (2013). Towards a "product design BCI" based on event-related potentials: Preliminary results and lessons learned. In *Proceedings of the Gmunden Retreat on NeuroIS*.

Wriessnegger, S. C., Hackhofer, D., Müller-Putz, G. R. (2015). Classification of unconscious like/dislike decisions: First results towards a novel application for BCI technology. In *Proceedings of the 37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society*.

Yilmaz, B., Korkmaz, S., Arslan, D. B., Güngör, E., & Asyali, M. H. (2014). Like/dislike analysis using EEG: Determination of most discriminative channels and frequencies. C*omputer Methods and Programs in Biomedicine, 113*, 705-713.

About the Authors

Gernot R. MÜLLER-PUTZ is head of the Institute for Knowledge Discovery and its associated BCI Lab. He received his MSc from Graz University of Technology in 2000, and finished his PhD in 2004, also at TU Graz. In 2008 he received the "venia docendi" for medical informatics at the faculty of computer science, TU Graz. Since October 2014, he has been full professor for semantic data analysis. He has gained extensive experience in the field of biosignal analysis, brain-computer interface research, EEG-based neuroprosthesis control, hybrid BCI systems, the human somatosensory system, and assistive technology over the past 15 years. He has also managed several national and international projects and is currently coordinator of a Horizon 2020 project, MoreGrasp. Furthermore, he has organized and hosted six international Brain-Computer Interface Conferences over the last 13 years in Graz, the last one taking place in September 2014. He is also steering board member for the International BCI Meeting, which takes place in the US usually every three years (last time in 2013). He is review editor of *Frontiers in Neuroprosthetics*, since 2014 he is Associate Editor of the *Brain-Computer Interface Journal* and of the *IEEE Transactions of Biomedical Engineering*.

René RIEDL is a professor for Digital Business and Innovation at the University of Applied Sciences Upper Austria and an associate professor for Business Informatics at the University of Linz. Moreover, he serves on the executive board of the Institute of Human Resources and Organizational Development in Management (IPO) at the University of Linz. He has published in the following outlets, among others: *Advances in Human-Computer Interaction, Behavior Research Methods, BMC Neurology, Business & Information Systems Engineering, Communications of the AIS, DATA BASE for Advances in Information Systems, Industrial Management & Data Systems, Journal of Computer Information Systems, Journal of Information Technology, Journal of Management Information Systems, Journal of Neuroscience, Psychology, and Economics, Journal of the Association for Information Systems*, and *MIS Quarterly*. He holds or has held various editorial positions (*AIS Transactions on Human-Computer Interaction, Business & Information Systems Engineering, DATA BASE for Advances in Information Systems, Information Systems Journal, Information Systems Research, Journal of Information Technology Theory and Application, Journal of Management Information Systems, MIS Quarterly,* and *Journal of the AIS*).

Selina Christin WRIESSNEGGER is Senior Postdoctoral Fellow of the Institute for Knowledge Discovery and member of the BCI Lab. She completed her diploma in Psychology at the University of Graz and her PhD at the Max-Planck-Institute for Human Cognitive and Brain Sciences in Munich. During her PhD, she was research assistant at Fondazione Santa Lucia (IRCCS) in Rome, Section Human Physiology, for one year. She has gained experience in analysing brain signals with different neuroimaging techniques like fMRI, fNIRS and EEG. Furthermore she is an expert in brain-computer interface research, statistics, human psychophysiology and cognitive neuroscience.