Introduction

NeuroIS is a field in Information Systems (IS) which makes use of neurophysiological tools and knowledge to better understand the development, adoption, and impact of information and communication technologies. The idea of applying physiological measurement in IS research is not a recent one. Galletta and colleagues, for example, already wrote more than 20 years ago that a “lack of actual measures” (p. 78) exists, and they suggested heart rate and hormone measurement, among others, as complements to the more traditional measurement techniques (Huston et al., 1993). However, despite the fact that a very limited number of publications on IS phenomena and neurophysiological measurement have been available for more than ten years, the idea of applying cognitive neuroscience approaches in IS research appeared at the 2007 International Conference on Information Systems (ICIS) and at pre-ICIS workshops (for details, see Riedl and Léger, 2016). Since that time, NeuroIS has been developing at a stunning pace.

A number of NeuroIS papers, both conceptual and empirical in nature, have been published in mainstream IS journals, including papers in premium outlets such as MIS Quarterly, Information Systems Research, Journal of Management Information Systems, and Journal of the Association for Information Systems. Analysis of the extant NeuroIS literature reveals that the papers vary in terms of the IS phenomena studied and the research tools employed. In a recent NeuroIS book, Riedl and Léger (2016) indicate that NeuroIS contributions address the following phenomena (topics), among others: attention and memory, avatars, business process modelling, e-commerce, emotions in human-computer interaction, enterprise systems, information behavior, IS design science, IT security, knowledge processes, mental workload, multitasking, music and user interfaces, neuro-adaptive systems, risk, social networks, software development, technology adoption and acceptance, technostress, trust, usability, virtual worlds, and website design. Moreover, based on an analysis of the extant literature, Riedl and Léger (2016) indicate that IS scholars have used a vast range of neurophysiological tools, such as functional magnetic resonance imaging (fMRI), electroencephalography (EEG), functional near-infrared spectroscopy (fNIRS), transcranial direct-current stimulation (TDCS), electrocardiogram (EKG), galvanometer (i.e., measurement of the conductance of the skin), oculometry and pupillometry (i.e., eye movement and pupil dilation measurement), and hormone measurement.
Against the background of the fact that NeuroIS has been established as a research field in the IS discipline in the past decade, it is useful to provide a reflection on the foundations and the status of the field. The present chapter has the goal to provide such a brief reflection. However, NeuroIS is a relatively young field, and hence we observe an ongoing development of concepts and methods. It follows that it is possible that concepts and methods that are considered essential today will become less important in the future. Likewise, new concepts and methods that have not yet received attention in the NeuroIS literature will eventually become crucial in the future. In other words, the author of this chapter believes that a final consolidation of the concepts and methods in the NeuroIS field has not yet taken place. This fact makes it even more interesting to observe, or to directly contribute to, the future development of the field. Thus, it is also hoped that the present chapter creates interest in NeuroIS.

What is NeuroIS?

This section gives an overview of the NeuroIS field, including its genesis in 2007. Other themes in this section are notes on foundations of human neurobiology and a brief description of reference disciplines of NeuroIS.

The idea of applying cognitive neuroscience approaches in IS research appeared at ICIS in December 2007. In his keynote presentation for the Sixth Annual Workshop on Human-Computer Interaction Research in Management Information Systems, a pre-ICIS event, Fred D. Davis, among other themes, outlined the potential of cognitive neuroscience for technology acceptance research. Two other presentations in this workshop also dealt with topics at the nexus of neuroscience and human-computer interaction (Adriane B. Randolph: paper 12, René Riedl: paper 15; see http://sighci.org/). Moreover, Angelika Dimoka presented an ICIS paper entitled “Neuro-IS: The Potential of Cognitive Neuroscience for Information Systems Research” in the track “Breakthrough Ideas in Information Technology” (Dimoka et al., 2007). Today, it is an established fact that these presentations in the context of ICIS 2007 constitute the genesis of the NeuroIS field.

Dimoka et al. (2007) defined the term NeuroIS as “the idea of applying cognitive neuroscience theories, methods, and tools in Information Systems (IS) research.” Later, based on a discussion of 15 IS and neuroscience scholars at the inaugural Gmunden Retreat on NeuroIS, an annual academic conference on research at the nexus of information systems and neuroscience (see www.neurois.org/), Riedl et al. (2010, p. 245) put forward the following definition:

NeuroIS is an interdisciplinary field of research that relies on knowledge from disciplines related to neurobiology and behavior, as well as knowledge from engineering disciplines. 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 such as health, well-being, satisfaction, adoption, and productivity.

Sound application of neuroscience approaches in IS contexts implies a reasonable degree of knowledge on human neurobiology. As outlined in more detail in Riedl and Léger (2016, Chapter 2), the ancient areas of history reveal evidence of human awareness of the brain. It follows that basic investigations into the anatomy and functions of the brain date back thousands of years, with significant scientific contributions starting after the Middle Ages. Hence, a vast amount of knowledge on human neurobiology exists today, documented in tens of thousands of journal articles and in a wealth of textbooks.
The human nervous system is necessary for perceptions, thoughts, feelings, and behavior and it consists of two parts: the central nervous system (CNS; brain and spinal cord) and the peripheral nervous system (PNS; neural tissue except for the CNS). Despite the fact that these two systems are anatomically separate units, their functions are interrelated. The PNS can be subdivided into the somatic nervous system (SNS) and the autonomic nervous system (ANS), and the latter consists of the sympathetic division (activates the body) and parasympathetic division (relaxes the body). Riedl et al. (2014) indicate that the brain (i.e., the information processing unit) and the ANS (i.e., the unit that keeps the body in balance; referred to as homeostasis) are the major units of analysis in NeuroIS research, while the spinal cord and the SNS are less important. A primer on neurobiology and the brain for information systems scholars is available in Riedl and Léger (2016, see chap. 2).

Figure 7.1 shows a conceptual illustration of the human nervous system; moreover, it shows that the human brain consists of four lobes (frontal, temporal, parietal, occipital), each of which is related to specific functions (example functions are indicated in Figure 7.1). However, it is important to note that a one-to-one mapping between a cognitive function and an anatomical region in the brain does not exist. Thus, the brain does not operate in a simple one-to-one fashion (Price and Friston, 2005). Today it is an established fact that a network of regions and the interaction between them are critical for the emergence of cognitive functions (Riedl et al., 2017a; see Appendix C in their paper, Sporns, 2011).

In addition to general knowledge of human neurobiology, research in several other scientific disciplines has revealed insights into biological foundations and applications relevant to IS research. Riedl and Léger (2016) analyzed various scientific disciplines and developed a

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*Figure 7.1* The human nervous system and brain lobes
Table 7.1 Important reference disciplines of NeuroIS

<table>
<thead>
<tr>
<th>Reference Disciplines</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cognitive neuroscience</td>
<td>A discipline geared toward understanding how the brain works, how its structure and function affect behavior, and ultimately how the brain enables the mind.</td>
</tr>
<tr>
<td>Neuropsychology</td>
<td>A discipline that holds the notion that the mind acts through the brain to produce higher functions, whereas the brain alone is responsible for lower functions that we have in common with other animals.</td>
</tr>
<tr>
<td>Neuroeconomics</td>
<td>A discipline with the objective to provide a single, general theory of human behavior for understanding the processes that connect sensation and action by revealing the neurobiological mechanisms by which decisions are made.</td>
</tr>
<tr>
<td>Neuromarketing</td>
<td>A discipline focused on the application of neuroimaging methods to product marketing.</td>
</tr>
<tr>
<td>Neuroergonomics</td>
<td>A discipline defined as the study of brain and behavior at work.</td>
</tr>
<tr>
<td>Affective computing</td>
<td>A discipline with the objective to positively influence effectiveness in human-computer interaction, based on the assignment of the human capabilities of observation, interpretation, and generation of emotional features to computers.</td>
</tr>
<tr>
<td>Brain-computer interaction</td>
<td>A discipline with the objective to provide a non-muscular channel for sending messages to the external world in order to provide a communication possibility for “locked in” patients (i.e., people who are completely paralyzed and unable to speak, but who are cognitively intact).</td>
</tr>
</tbody>
</table>

Note: Sources of definitions can be found in Riedl and Léger, 2016, section 1.3.

list of reference disciplines of NeuroIS. Among others, cognitive neuroscience, neuropsychology, neuroeconomics, decision neuroscience, social neuroscience, consumer neuroscience, neuroergonomics, affective computing, and brain-computer interaction have been identified as important reference disciplines. Table 7.1 summarizes the disciplines.

Why is NeuroIS important?

Based on Riedl and Léger (2016), this section outlines ten contributions available from the application of neurobiological approaches to IS research and practice. Each contribution is explained based on a concrete example. Examples include both published research and research ideas.

1 The neuroscience literature can inform the design of IT artifacts, as well as IS investigations in general (e.g., by motivating behavioral experiments), and can do so without application of neuroscience methods and tools.

Example: Brain research indicates that humans have a preference toward curved objects, if compared to sharp-angled objects, because perception of the latter may result in activation of the amygdala (Bar and Neta, 2007). This brain area is related to arousal, threat, and fear. Based on this brain research knowledge, a recommendation for software engineers could be to avoid using sharp-angled objects on a graphical user interface (e.g., button
design). This, in turn, is expected to prevent negative user feelings, and fewer negative responses are likely to positively affect important outcome variables, such as user satisfaction.

2 Brain activity, or any other neurophysiological activation (e.g., hormones, heart rate, skin conductance, pupil dilation, or muscle tension), can be used as a mediator between the IT artifact and IT behavior or antecedents of IT behavior (e.g., beliefs or behavioral intentions), thereby introducing a biological level of analysis and explaining why and how an IT artifact influences the IT behavior or its antecedents.

Example: Technostress has become an important research topic in IS research (e.g., Riedl et al., 2012, Tams et al., 2014). Computer hassles, such as system breakdowns or long and variable response times, are an important stress factor in human-computer interaction. Researchers have studied the effects of computer hassles on physiological activation of the user and subsequent IT behavior, as well as antecedents of IT behavior (for a review, see Riedl, 2013).

3 Application of neuroscience and psychophysiological methods and tools can shed light on theoretical mechanisms underlying the influence of the IT artifact on IT behavior or antecedents of IT behavior.

Example: Consider that experimental research reveals that the integration of a trust seal into an e-commerce environment positively influences purchase intention. While it is not difficult to establish such a research finding, determination of the reason of this effect is a more sophisticated task because alternative explanations may result in this finding. On the one hand, it is possible that the trust seal reduces a user’s uncertainty perceptions. On the other hand, it is also possible that the seal increases the trustworthiness of the online shop. Because it is, at least in some cases, difficult to investigate specific phenomena (including uncertainty and trust) based on self-report questionnaires, application of neuroscience tools may lead to novel theoretical insights. Because neural correlates of uncertainty and trustworthiness have already been identified in neuroscience research, these findings could shed light on the question of whether reduced uncertainty or increased trustworthiness has led to the influence of the trust seal on purchase intention. A NeuroIS study could reveal activation of the neural correlates of trustworthiness. All other things being equal, this would suggest that elevated purchase intention is a result of increased trustworthiness perceptions.

4 Brain activity, or any other biological activation, can be used to inform IT artifact evaluation.

Example: Brain research has found that trust is associated with activity in the caudate nucleus (for a review, see Riedl and Javor, 2012). Software developers could implement two prototypes of a user interface and evaluate the trust-inducing potential of each version, based on fMRI. Moreover, EEG research identified neural correlates of cognitive workload (for a review, see Müller-Putz et al., 2015). Developers could evaluate the cognitive workload effects of different prototypes.

5 Neuroscience and psychophysiological methods and tools make possible the measurement of constructs that cannot be reliably measured on the basis of self-report techniques such as interviews or questionnaires.

Example: Flow is a mental state in which an individual performing an activity is immersed in a feeling of focus, complete involvement, and enjoyment in the process of the activity.
It follows that the measurement of flow based on questionnaire is difficult because, at least in case of concurrent measurement, the flow necessarily becomes interrupted. Mauri et al. (2011) have used a combination of neurophysiological measures to evaluate the flow state of Facebook users, and their results show that physiological activation patterns can be used to explain Facebook’s success.

Biological states and processes can be better predictors of behaviorally relevant outcome variables (e.g., user health) than self-report measures.

*Example:* Medical evidence indicates that repeated and chronic elevations of stress hormones may have detrimental health effects (see, for example, the review by Riedl, 2013, which shows reports on the stress hormones adrenaline and cortisol). Also, it is an established fact that conscious perception of stress, measured by means of questionnaires, frequently does not significantly correlate with the unconscious elevations of stress hormones (e.g., Tams et al., 2014). This finding suggests that hormone measurements are better predictors of future health states than self-reports. Yet, it is important to note that the best way to predict dependent variables is often to use complementary forms of measurement.

Neuroscience and psychophysiological methods and tools make possible an understanding of whether the use of IT artifacts alters the brain, and if so, how this occurs.

*Example:* It is reported that IT use may lead to addiction, and that this behavioral addiction is based on structural and/or functional changes in the brain (He et al., 2017, Montag and Reuter, 2015).

Biological states and processes can be used in real time to design adaptive systems that may positively affect practically relevant outcome variables such as health, well-being, satisfaction, and productivity.

*Example:* It has been demonstrated that bio-signals indicating the cognitive and affective states of users (e.g., facial expressions, pupil dilation, skin conductance, or brain waves) may be automatically monitored so that a neuro-adaptive system can dynamically adapt the interface to a user’s states. Adam et al. (2016), for example, present a design blueprint for stress-sensitive adaptive enterprise systems; one of the major characteristics of this blueprint is the use of neurophysiological measures (e.g., skin conductance) as real-time stress indicators.

Provision of real-time information on a user’s own biological state, based on a specific physiological indicator, constitutes an important foundation for a user to consciously control the physiological indicator. Such biofeedback systems may have positive effects on outcome variables such as health or performance.

*Example:* If a person observes his or her own level of arousal (e.g., in the form of a graph on a computer screen) based on real-time measurement of the arousal state with non-obtrusive measures (e.g., skin conductance), this greater awareness improves conscious control of the arousal level. Arousal has a significant influence on human performance (Yerkes and Dodson, 1908); thus, users may benefit from biofeedback systems.

Electrophysiological measures of brain function can be used to replace input devices (e.g., mouse or keyboard) in human-computer interaction, which may positively affect outcome variables such as enjoyment or productivity.
Example: Navigation in virtual worlds is possible through BCI technologies (e.g., Scherer et al., 2008). A long-term goal of brain-computer interaction (BCI) research in the business domain has been proposed (Byrne and Parasuraman, 1996; Lee and Tan, 2006; Loos et al., 2010; Riedl, 2009), namely that such systems may contribute to the automatization of process steps in workflows (e.g., a system recognizes a user’s intentions and information processing begins automatically).

What are possible NeuroIS topics?

In the previous section, several NeuroIS topics have already been outlined. This section provides a brief publications retrospective of NeuroIS papers. The identification of the research topics, and the neuroscience tools that have been applied to examine the topics, is based on analysis of papers published between 2010 and 2016. The following discussion is illustrative. It follows that this brief review of papers is not exhaustive.

Based on fMRI, Dimoka (2010) found that trust in online environments is related to the brain’s reward (caudate nucleus, putamen), prediction (anterior paracingulate cortex), and uncertainty areas (orbitofrontal cortex), while distrust is related to the brain’s emotion (amygdala) and fear of loss areas (insula cortex). Moreover, this study found that the identified brain areas may predict price premiums in simulated online shopping and the levels of brain activation have a stronger predictive power than the corresponding self-report measures. Using the same brain imaging technique, Riedl et al. (2010) examined gender differences in online trust and found some similarities (e.g., insula cortex related to disgust, uncertainty, or anticipation of pain) and substantial differences (e.g., caudate nucleus, putamen, and thalamus related to reward, or prefrontal structures related to anticipation of future decision consequences, or hippocampus related to memory) between neural processing in women and men. In a further fMRI study, Riedl et al. (2014) studied trust in avatars and humans. Findings indicate that people are better able to predict the trustworthiness of humans than the trustworthiness of avatars. Moreover, it was found that decision making about whether or not to trust another actor activates the medial frontal cortex significantly more during interaction with humans, if compared to interaction with avatars (note that this brain region is of high importance for the prediction of other individuals’ thoughts and intentions, referred to as mentalizing, a crucial ability in trust situations). Finally, results indicate that the trustworthiness learning rate is similar, whether interacting with humans or avatars.

In addition to trust studies, several NeuroIS papers examined stress and arousal. Nunemaker et al. (2011) developed and evaluated an automated kiosk that uses embodied intelligent agents to interview individuals and detect changes in arousal, behavior, and cognitive effort by using psychophysiological information systems. In essence, the authors describe the contribution of their study as follows:

[T]his research demonstrates how even a single sensor [measuring vocal pitch, people speak with a higher pitch and with more variation in pitch or fundamental frequency when under increased stress or arousal], properly modeled, can provide... awareness of human emotion or behavior.

(p. 42)

Riedl et al. (2012) examined user stress resulting from system breakdown. Using salivary measurement of the stress hormone cortisol, it was found that system breakdown in the form
of an error message is an acute stressor that may elicit cortisol elevations as high as in non-HCI (human-computer interaction) stress situations such as public speaking. In a similar experiment, Riedl et al. (2013) studied the role of gender in computer users’ physiological reactions to malfunctioning technology. Based on theories explaining that men, in contrast to women, are more sensitive to “achievement stress,” they hypothesized that, in cases of system breakdown during execution of a human-computer interaction task under time pressure (as compared to a breakdown situation without time pressure), male users would exhibit higher levels of stress than women. Using electrodermal activity as a stress indicator, the hypothesis was confirmed.

Astor et al. (2013) developed and evaluated a neuro-adaptive system in a financial decision-making context, based on unobtrusive and real-time heart rate measurement. Their study demonstrated the efficacy of a biofeedback-based NeuroIS tool aimed at supporting decision makers with improving emotion regulation capabilities. In another study on technostress, Tams et al. (2014) examined effects of stress on performance on a computer-based task. This study showed that physiological and self-report measures can diverge. Importantly, this divergence precludes them from constituting alternative forms of measurement; rather, both forms of measurement seem to be complementary. This complementarity was demonstrated by using the physiological measure (salivary alpha-amylase, a precursor substance of a major stress hormone in the human body) to explain additional variance in performance on a computer-based task, variance to which the self-reported stress measure was blind. Thus, the authors concluded that “the value of NeuroIS research lies in its capacity to complement traditional IS methods so that a more complete understanding of IS phenomena can be obtained and more powerful predictive relationships achieved” (p. 744).

Léger et al. (2014a) report on an experiment that used an enterprise resource planning (ERP) system in a decision-making context to investigate differences between the emotional responses of expert and novice users. Specifically, it was examined how such a difference affects information sourcing behavior. In a simulated ERP business environment (i.e., SAP), subjects’ emotional responses during business decisions were measured based on electrodermal activity recording. Results show that both expert and novice SAP users exhibit significant electrodermal activity during their interaction with SAP, showing that ERP use can be an emotional process for both groups. Moreover, results show that experts’ emotional responses lead to their sourcing information from SAP, while novices’ emotional responses lead to their sourcing information from other people. Altogether, Léger et al. (2014b) concluded that emotions can lead to different behavioral reactions, depending on whether the user is an expert or novice.

In another stream of research based on EEG, Gregor et al. (2014) examined user emotions during interaction with websites. They found that positive and negative emotion-inducing stimuli were associated with positive and negative emotions when viewing the websites; note that emotions were measured based on self-reports and EEG data. Findings also indicate that the EEG measure had some predictive power for the outcome variable e-loyalty. Li et al. (2014) examined user game engagement through software gaming elements. Findings demonstrated that cognitive-related gaming elements (classified as game complexity and game familiarity) influence the density of theta oscillations from the left side of the dorsolateral prefrontal cortex and game engagement.

Hu et al. (2015) studied information security and self-control. Using event-related potentials, an EEG-based technique, findings indicate that subjects with low self-control had lower levels of neural recruitment in both hemispheres relative to those with high self-control, in
particular with respect to areas in or near the dorsal lateral prefrontal cortex and inferior frontal cortex. The authors argue that their study extend[s] the findings in neuroscience literature related to the role of self-control in decision making in general, and validate a new paradigm for use with the electroencephalography/event-related potentials (EEG/ERP) technique to examine theoretical questions in information security and criminology research.

(p. 7)

Another study also examined information security. Specifically, Vance et al. (2014) studied users’ perception of and response to information security risks. Findings indicate that participants’ P300 amplitude, a specific EEG measure, in response to losses in a risk-taking experimental task strongly predicted security warning disregard in a subsequent and unrelated computing task. Importantly, self-reported measures of information security risk did not predict security warning disregard. The study also found that after simulating a malware incident on the participants’ computing devices, post-test measures of information security risk perception did predict security warning disregard. Thus, the results of this experiment suggest that self-reported measures of information security risk can significantly predict security behavior, but only when security risks are salient. In contrast, the P300, an EEG-based risk measure in this study, was a significant predictor of security behavior both before and after the security incident. The authors concluded that their results “highlight the robustness of NeuroIS methods in measuring risk perceptions and their value in predicting security behavior” (p. 704).

A recent fMRI study by Warkentin et al. (2016) on the neural correlates of protection motivation for secure IT behaviors confirms the assessment of Vance and colleagues that NeuroIS methods may provide significant value to IT security researchers.

In addition to trust, technostress and arousal, and security, IS researchers have examined several other topics based on neurophysiological measurement. Léger et al. (2014a) used frequency analysis to examine the neural correlates of cognitive absorption in the context of IS training. Results indicate that subjects with high EEG Alpha and low EEG Beta (indicating calmness, relaxation, and low vigilance) reported being more cognitively absorbed than subjects who did not display these patterns.

So far, I discussed different NeuroIS topics based on example studies. A more systematic review of NeuroIS research is provided in Riedl and Léger (2016, section 4.2). This review classified 76 papers published in the 2011–2014 proceedings of the Gmunden Retreat on NeuroIS (for details, see www.neurois.org/). Classification is based on four categories described in Dimoka et al. (2012, p. 691): cognitive processes, emotional processes, social processes, and decision-making processes. Table 7.2 summarizes the main results of this analysis.

Cognition and emotion, importantly, are involved in both social and decision-making processes. It follows that the results indicate that NeuroIS research has thus far explored only the two fundamental processes, namely cognition and emotion, and has not yet comprehensively investigated their application with regard to social and decision-making processes. Because both social neuroscience and decision neuroscience are two fields which have been developing at a stunning pace, it is likely that future NeuroIS research will also study social and decision-making processes more intensively (because a wealth of relevant research findings are available in social neuroscience and decision neuroscience).

With respect to the adoption rate of neuroscience tools, Riedl and Léger (2016), based on their analysis of papers published in the proceedings of the Gmunden Retreat on NeuroIS, found the following result: (1) EEG, (2) eye-tracking (including pupillometry),
Table 7.2 Results of NeuroIS paper classification (N = 76)

<table>
<thead>
<tr>
<th>Category</th>
<th># Papers</th>
<th>Percent</th>
<th>Example Topics</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cognitive</td>
<td>33</td>
<td>43%</td>
<td>Information search, mental workload in HCI</td>
</tr>
<tr>
<td>Emotional</td>
<td>30</td>
<td>39%</td>
<td>Technostress, website impression formation</td>
</tr>
<tr>
<td>Social</td>
<td>11</td>
<td>14%</td>
<td>Trust, coordination in IS initiatives</td>
</tr>
<tr>
<td>Decision-making</td>
<td>2</td>
<td>3%</td>
<td>Online payment method choice, risk processing</td>
</tr>
<tr>
<td>Sum</td>
<td>76</td>
<td>100%</td>
<td></td>
</tr>
</tbody>
</table>

Note: Original data of this analysis can be found in Riedl and Léger, 2016, section 4.2. Sum of percents of rows is not 100% due to rounding differences. HCI: Human-Computer Interaction.

(3) electrodermal activity, (4) fMRI, (5) metrics related to heart rate, and (6) hormone assessment. Other tools (e.g., fNIRS) have been applied less frequently. It follows that NeuroIS researchers have applied tools related to both measurement of CNS activity (e.g., EEG, fMRI, or fNIRS) and measurement of ANS activity (e.g., pupillometry, electrodermal activity, metrics related to heart rate, or hormone measurement). I consider this variety as a major strength of the NeuroIS field.

How to conduct NeuroIS research?

This section gives an overview of important concepts of a NeuroIS research methodology. I start this section with a brief summary of major neurophysiological tools (see Table 7.3). More comprehensive tool descriptions are provided in Riedl et al. (2010), Dimoka et al. (2012), and particularly in Riedl and Léger (2016, see chap. 3).

Table 7.3 shows that each NeuroIS tool is either related to measurement of CNS or ANS activity. Moreover, it is also shown what specific parameter a tool actually measures. As an example, fMRI and fNIRS do not directly measure neuronal activity. Rather, neuronal activity is inferred based on other physiological indicators. Also, Table 7.3 shows an assessment of a tool’s intrusiveness and the costs of application. Note that the main goal of this classification is to give the reader an impression of the relative intrusiveness and costs. As explained in detail in Riedl et al. (2014, section 5.6), intrusiveness can be conceptualized with three dimensions: degree of movement freedom during task execution, degree of natural position during task execution (which is usually a sitting or standing position in human-computer interaction), and degree of invasiveness (defined as the extent to which the recording device of a measurement instrument has to be inserted into or attached to the body).

Based on the notion that NeuroIS researchers deliberately select a tool in a specific research situation, a number of papers have been published that deal with specific guidelines. Dimoka (2012) published guidelines for conducting fMRI studies in social science research. These guidelines were later complemented by Hubert et al. (2012, 2017) who introduced connectivity analysis of brain imaging data to NeuroIS research. Gefen et al. (2014) discuss the potential role of fNIRS in IS research. In another paper, Léger et al. (2014c) introduced the Eye-Fixation Related Potential (EFRP) method to IS research. The EFRP method allows synchronization of eye-tracking data with EEG recordings to precisely capture users’ neural activity at the exact time when processing of a stimulus begins (e.g., processing an event on the screen.). In essence, EFRP complements and overcomes shortcomings of the traditional ERP method, which can only stamp the time at which a stimulus is presented to a user. It follows that the
EFRP method increases preciseness of measurement in NeuroIS research. Müller-Putz et al. (2015) discuss EEG as a research tool in the IS discipline, and specifically deal with the tool’s foundations, measurement principles, and applications in the IS field.

Moreover, vom Brocke and Liang (2014) have published general guidelines for neuroscience studies in IS research. In essence, this paper takes an IS perspective in deriving six phases for conducting NeuroIS research and describes five guidelines for planning and evaluating NeuroIS studies: to advance IS research, to apply the standards of neuroscience, to justify the choice of a neuroscience strategy of inquiry, to map IS concepts to bio-data, and to relate the experimental setting to IS-authentic situations.

Riedl et al. (2014), in a paper titled “Towards a NeuroIS Research Methodology: Intensifying the Discussion on Methods, Tools, and Measurement,” argue that six factors with respect to a measurement instrument, among others that will become evident in future discussions, are

<table>
<thead>
<tr>
<th>Tool measures . . .</th>
<th>Intrusiveness</th>
<th>Costs of application</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Tools related to CNS activity measurement</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>fMRI</td>
<td>Neural activity is inferred based on magnetic properties of oxygenated and deoxygenated blood in the brain</td>
<td>high</td>
</tr>
<tr>
<td>fNIRS</td>
<td>Neural activity is inferred based on oxy-hemoglobin and deoxy-hemoglobin concentration changes in the cortical tissue of the brain</td>
<td>medium</td>
</tr>
<tr>
<td>PET</td>
<td>Neural activity is inferred based on metabolic activity (visualized by injection of radioactive isotopes)</td>
<td>high</td>
</tr>
<tr>
<td>EEG</td>
<td>Measurement of electrical activity on the scalp, which constitutes the manifestation of the activity of populations of neurons in the brain</td>
<td>medium</td>
</tr>
<tr>
<td>MEG</td>
<td>Measurement of magnetic fields induced by activity in the brain</td>
<td>high</td>
</tr>
<tr>
<td><strong>Tools related to ANS activity measurement</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>EDA</td>
<td>Measurement of the conductance of the skin in a specific context, or in response to a particular stimulus (often measured in the palm of the hand)</td>
<td>low</td>
</tr>
<tr>
<td>EKG</td>
<td>Measurement of electrical activity of the heart on the skin</td>
<td>low</td>
</tr>
<tr>
<td>Pupillometry</td>
<td>Measurement of pupil dilation</td>
<td>low</td>
</tr>
<tr>
<td>fEMG</td>
<td>Measurement of electrical activity resulting from contraction and relaxation of facial muscles</td>
<td>medium</td>
</tr>
<tr>
<td>Hormone assessment</td>
<td>Measurement of hormones in blood, saliva, or urine</td>
<td>low (except drawing of blood samples)</td>
</tr>
</tbody>
</table>
critical for a rigorous NeuroIS research methodology. The six factors are (definitions taken from Riedl et al., 2014, p. xxix):

1. **Reliability**: The extent to which a measurement instrument is free of measurement error, and therefore yields the same results on repeated measurement of the same construct.
2. **Validity**: The extent to which a measurement instrument measures the construct that it purports to measure.
3. **Sensitivity**: A property of a measure that describes how well it differentiates values along the continuum inherent in a construct.
4. **Diagnosticity**: A property of a measure that describes how precisely it captures a target construct as opposed to other constructs.
5. **Objectivity**: The extent to which research results are independent from the investigator and reported in a way so that replication is possible.
6. **Intrusiveness**: The extent to which a measurement instrument interferes with an ongoing task, thereby distorting the investigated construct.

Riedl et al. (2014) argue that NeuroIS researchers – independent from whether their role is editor, reviewer, or author – should carefully give thought to these factors.

**Concluding comments**

The genesis of NeuroIS took place in 2007. Since then, a number of IS scholars have started to use concepts and tools from neuroscience to better understand human cognition, emotion, and behavior in IS contexts. In my opinion, the NeuroIS field has developed at a stunning pace in the past decade. As outlined in this paper, a number of IS topics have been studied based on a variety of neuroscience tools. Moreover, several conceptual papers and a recent textbook (Riedl and Léger, 2016) have discussed the great potential of neuroscience for IS research. Also, papers contributing to the methodological development of the field were published. However, despite these positive developments in the past, recent evidence (Riedl et al., 2017b) indicates that the NeuroIS field is still in a relatively nascent stage. Therefore, it is critical that more IS scholars get engaged in NeuroIS, thereby increasing the number of community members who are potential editors, reviewers, and authors. Importantly, newcomers must become familiar with the basic theories, concepts, methods, tools, and measurements that are used in cognitive neuroscience, neurobiology, and psychophysiology. Based on a higher degree of familiarity, IS scholars can better evaluate whether or not a specific theory, concept, method, tool, or measurement is suitable to study a specific IS research question, or may form the basis for the development of a neuro-adaptive information system. It is hoped that increasingly more IS scholars will recognize the indisputable potential of neuroscience for IS research and will be able to develop the knowledge and infrastructure basis to conduct high-quality NeuroIS research. It will be rewarding to see what insights future research will reveal.

**References**


