A Decade of NeuroIS Research: Status Quo, Challenges, and Future Directions

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Abstract

NeuroIS is a field in Information Systems (IS) that makes use of neuroscience and neurophysiological tools and knowledge to better understand the development, adoption, and impact of information and communication technologies. The fact that NeuroIS now exists for approximately ten years motivated us to comprehensively review the academic literature. Investigation of the field’s development provides insights into the status of NeuroIS, thereby contributing to identity development in the NeuroIS field. Based on a review of N = 164 papers published in 55 journals and 11 conference proceedings, we addressed the following four research questions: Who published NeuroIS research? What kind of NeuroIS research was published? Which major thematic orientation was chosen by NeuroIS researchers? How was the empirical NeuroIS research conducted? Based on a discussion of the findings and their implications for future research, we conclude that today NeuroIS can be considered as established research field in the IS discipline.

Keywords: Brain, EEG, Electrodermal Activity, Eyetracking, fMRI, Heart Rate, Nervous System, NeuroIS, Neuroscience, Review
Introduction

NeuroIS is a field in Information Systems (IS) that makes use of neuroscience (e.g., functional magnetic resonance imaging, fMRI, or electroencephalography, EEG) and neurophysiological (e.g., electrodermal activity, EDA, or heart rate, HR) tools and knowledge to better understand the development, adoption, and impact of information and communication technologies (Dimoka et al. 2007, 2011; Dimoka et al. 2012; Riedl et al. 2010a, Riedl et al. 2017). According to Riedl and Léger (2016, pp. 73-74), the genesis of NeuroIS took place at the International Conference on Information Systems (ICIS) in 2007, and the term “NeuroIS” was coined by Dimoka et al. (2007).

In the last ten years, NeuroIS has attracted significant attention in the IS discipline. Top journals such as the Journal of Management Information Systems (Vol. 30, No. 4, 2014) and the Journal of the Association for Information Systems (Vol. 15, No. 10, 2014) published NeuroIS special issues, and some brain imaging studies have appeared in the premier journals of the IS discipline, such as Dimoka (2010) and Riedl et al. (2010b) in MIS Quarterly and Jenkins et al. (2016) in Information Systems Research. Moreover, NeuroIS panels were held at ICIS 2009 (Dimoka et al. 2009) and ICIS 2010 (Dimoka et al. 2010).

Recently, NeuroIS has also begun to attract attention beyond the IS discipline’s boundaries. As an example, the Association for NeuroPsychoEconomics states on its website that NeuroIS submissions are welcome, in addition to research from fields such as neuroeconomics, neuromarketing, neurofinance, and decision neuroscience (for details, please see http://www.neuropsychoeconomics.org/, last access on May 2, 2017). Moreover, NeuroIS research has been published in interdisciplinary journals, such as Javor et al.’s (2016) PLoS ONE paper on Parkinson Patients’ trust in avatars, or He et al.’s (2017) Scientific Reports paper on brain anatomy alterations associated with Social Networking Site addiction.

The fact that NeuroIS now exists for approximately ten years motivated us to comprehensively review the academic literature. Such a review is urgently needed because the status of the field has not been comprehensively evaluated thus far. We are aware of a review of “85 papers published in the 2011–2014 proceedings [of the Gmunden Retreat on NeuroIS, which] coded information on the topics as well as the methods and tools used in the studies” (Riedl and Léger 2016, p. 77). Moreover, a “review of empirical NeuroIS literature” that comprises 15 papers published in IS journals in the period 2010–2014 exists (see Appendix A in Riedl et al. 2017). However, we are not aware of a paper which comprehensively reviewed the NeuroIS literature published in academic journals and in the proceedings of mainstream conferences such as ICIS that spans the complete existence period of NeuroIS. We argue that for NeuroIS research to progress, such a comprehensive review, along with a critical evaluation of the field, is essential.

Examination of the field’s development may provide valuable insights into the future development of NeuroIS. In an essay on the identity of the IS discipline, Klein and Hirschheim (2008, p. 298) write: “[Research] provides philosophical support for our contention of the relationship between having a shared history and forming a strong identity and belonging [...] theory of understanding [...] contends that a shared sense of history provides the ultimate grounding and background information (pre-understanding) for communication in large and diverse collectives such as societies (and by extension to diverse disciplines)”. Bearing this argumentation in mind, the main motivation of the present study is to provide insights into the status of NeuroIS, thereby contributing to identity development in the NeuroIS field. Knowing one’s history, even if it is short, facilitates identity formation by identification of emergent thematic and methodological patterns and description of pressing issues; and knowing one’s past is important for coping with future challenges (Webster and Watson 2002).

Based on systematic analysis of the NeuroIS literature published in peer-reviewed academic journals and conference proceedings, in the present paper we specifically address the following research questions:

- **Who published NeuroIS research?**

  An answer to this question reveals the most productive authors in the NeuroIS field. Among other reasons, this analysis is valuable because it offers an objective basis for editors-in-chief and senior editors to identify qualified scholars who could become future associate editors or even senior editors to handle NeuroIS submissions. Moreover, this analysis enables both senior editors and associate editors to identify reviewers with NeuroIS experience.
What kind of NeuroIS research was published?

An answer to this question reveals the type of contribution of a NeuroIS paper. In essence, as described in more detail in the section “Literature Analysis”, a paper may offer one of the following five contributions: empirical study (completed), empirical study (research-in-progress), methodological paper (e.g., papers outlining how to apply a specific neuroscience tool), conceptual paper (e.g., papers discussing potential contributions of neuroscience to IS research), and reviews (i.e., papers focusing on the analysis of previous research).

Which major thematic orientation was chosen by NeuroIS researchers?

Based on a 4-category taxonomy developed by Dimoka et al. (2011, p. 691), which has already been applied to categorize NeuroIS publications (see Riedl and Léger 2016, p. 78), an answer to this question reveals the major themes in NeuroIS research. The four categories are: cognitive processes, emotional processes, social processes, and decision-making processes.

How was the empirical NeuroIS research conducted?

An answer to this question reveals various methodological aspects. In essence, as described in more detail in the section “Literature Analysis”, important methodological aspects that we analyzed are: used tool (e.g., fMRI, EEG, EDA, eyetracking), setting of a study (laboratory or field), time scale (longitudinal or cross-sectional), country of investigation, sample size, gender distribution in the sample, and age distribution in the sample.

The remainder of this article is structured as follows: In the next section, we present the methodology of the literature review. Then, we present major findings. Afterwards, we discuss the key findings and their implications for future NeuroIS research. Also, we outline limitations, and we close with a concluding statement.

Methodology of the Literature Review

Literature Search

In order to identify NeuroIS publications, we conducted a literature search and considered peer-reviewed journal and conference publications that have been published since the term “NeuroIS” has originally been coined in December 2007 (Dimoka et al. 2007). This search process was conducted in the period November 2016–January 2017. Hence, our review comprises publications from 2008 to 2016 (note that in this review we also cite 2017 and forthcoming NeuroIS papers; yet, they are not a formal part of the review).

Keywords for the literature search were derived from landmark publications that offer an introduction to the field of NeuroIS. In particular, we drew upon Dimoka et al. (2007, 2011, 2012), Riedl et al. (2010a), and Riedl and Léger (2016). We used generic terms representing the field as a whole such as “NeuroIS”, “Neuroscience”, and “Nervous system” for our literature search, but also terms that are representative of the tools that are highlighted in these landmark publications such as “eye” (for eyetracking techniques) or “heart” (for cardiovascular measures). Because the human nervous system consists of two parts, the central nervous system (CNS; brain and spinal cord) and the peripheral nervous system (neural tissue except for the CNS, including the autonomic nervous system, ANS), and because hormone measurement based on blood, saliva, or urine samples also plays a role in NeuroIS research (Riedl 2013), we structure the keywords along four dimensions (generic terms, CNS terms, ANS terms, hormone terms; see Table 1). Outlets selected for our search process included all journals included in the Senior Scholar’s Basket of the Association for Information Systems (AIS), as well as other academic journals and AIS conferences (see http://aisnet.org/, last access on May 2, 2017). In total, the literature basis of our review includes 55 peer-reviewed journals and 11 peer-reviewed conference proceedings (listed in the Appendix). We believe that an analysis of 66 outlets over the entire existence period of the NeuroIS field constitutes a solid basis to draw conclusions about the status of the field. Note that our analysis does not cover, for two reasons, the papers published in the Proceedings of the Gmunden Retreat on NeuroIS, an “annual conference [that] has the objective to promote the successful development of the NeuroIS field” (Davis et al. 2016, p. v). First, Riedl and Léger (2016, pp. 77-83) already reviewed 85 papers from these proceedings. Second, many papers presented at this conference, based on the received feedback, are further developed into journal papers, and hence became part of our analyzed sample anyway.
For the present review, we used the most recent IS journal and conference proceedings ranking of the German Academic Association for Business Research (VHB) as a basis. This ranking covers mainstream IS journals and conference proceedings (for details, see http://vhbonline.org/vhb4you/jourqual/vhb-jourqual-3/teilrating-wi/). Search in journals was mainly conducted using the search function offered by the journal, though in some cases manual search throughout all issues from 2008 was carried out for efficiency purposes (e.g., in journals with a small number of issues such as the AIS Transactions on Enterprise Systems). For conference proceedings, we mainly searched manually, and only used keyword-based search in the few cases in which a search function was offered (e.g., in the AIS Electronic Library or SpringerLink). Publications for this review were selected based on their title and abstract from a total of approximately 25,000 hits that resulted from automated search, plus several hundred additional publications through which we searched manually.

As we focus on IS publications, our review does not include publications with research objectives that are predominantly relevant in computer science, such as studies on neuroscience data analysis techniques (e.g., specific machine learning algorithms) or prototypes of neural engineering technology (e.g., brain-computer interfaces). Moreover, as we are mainly interested in the business context, we also excluded studies on topics such as video gaming activities or virtual reality without recognizable reference to business (e.g., papers on flight simulators or simulations for surgical training were not included in the review).

Based on our review approach, we identified N = 164 NeuroIS publications (95 journal publications, 69 conference publications), of which N = 103 publications are completed empirical studies (72 journal publications and 31 conference publications). All 164 publications are listed in the References (marked with an asterisk).

**Literature Analysis**

In this section, we describe how we have conducted the literature analysis. In a first step, the documentation of relevant information was carried out by the second author of this paper. In those cases in which the second author was not completely sure how to classify a specific paper (this only happened in a few cases in which descriptions in the papers left room for interpretation), the first author (a person with two decades IS research experience and with long-standing experience in NeuroIS research) carried out the classification. In a second step, the first author reviewed all classification results of the second author, and consensus was ultimately reached on all classifications through discussion. This methodological approach was chosen to secure reliability.

Importantly, almost all aspects that we documented (see the bullet points in the next four subsections) constitute **facts without any subjective interpretation**. Thus, the first author’s revision of the second author’s documentation and classification was predominantly carried out for verification purposes of facts (e.g., because it is not possible to rule out mistakes in entry of data into the spreadsheet file that we used as documentation basis). Discussion to reach consensus was only necessary in a few cases and concerned setting of a study and time scale (see the section “How was the empirical NeuroIS research conducted?”). Moreover, discussion was also necessary in some cases in which we classified papers into high-level...
topical abstractions as described in Dimoka et al. (2011) (see the section “Which topics were addressed by NeuroIS research?”).

In the following, we outline the specific aspects that we documented, structured along the four research questions presented in the Introduction. An overview of our research questions and corresponding metrics is given in Table 2.

<table>
<thead>
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<th>Question</th>
<th>Metrics</th>
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| Who published NeuroIS research? | • Author names  
• Number of authors of each paper |
| What kind of NeuroIS research was published? | • Contribution: empirical study (completed), empirical study (research-in-progress), methodological paper, conceptual paper, review |
| Which major thematic orientation was chosen by NeuroIS researchers? | • Thematic orientation (based on Dimoka et al. 2011): cognitive processes, emotional processes, social processes, decision-making processes |
| How was the empirical NeuroIS research conducted? | • Neurophysiological tools used  
• Setting: field or laboratory  
• Time scale: longitudinal or cross-sectional  
• Country of investigation  
• Sample: size, gender distribution, age distribution |

**Who published NeuroIS research?**

A fundamental question in the evaluation of the status of the NeuroIS field concerns the scholars who are engaged in NeuroIS research. Based on the information provided in each paper (typically on the first page of a publication), we documented:

• All author names (last name and first name) and  
• Number of authors of each paper.

Riedl and Léger (2016) argue that “planning and conducting empirical NeuroIS research is a relatively time-consuming process, typically involving division of labor among the participating researchers” (p. 83). It follows that documentation of the number of authors provides valuable information on the status of the field, because a low number would contradict the “Division of labor” statement. Moreover, knowing the most productive authors in the NeuroIS field constitutes valuable information for journal editors (e.g., to recruit reviewers). The basis for the documentation was N = 164 publications.

**What kind of NeuroIS research was published?**

To classify the contribution of each publication (N = 164), we used one of five categories:

• Empirical study (completed): Papers in this category focus on empirically testing the relationship between at least two variables and feature information on their study design including data collection and analysis procedures, as well as the results of their investigation.

• Empirical study (research-in-progress): These papers are also empirical in nature, but do not have all characteristics of a completed empirical study. Such papers typically only report preliminary results, or present their study design without having collected or completely analyzed data.

• Methodological paper: Papers in this category describe new or existing neuroscience tools, as well as methodological approaches (e.g., for analysis of neurophysiological data), which are relevant to NeuroIS research. Examples are introductions to neuroscience tools such as EEG (e.g., Müller-Putz et al. 2015), methodological frameworks (e.g., Adam et al. 2011), or general methodological discussions with an example study (e.g., Tams et al. 2014).
• Conceptual paper: These papers discuss potential topics for NeuroIS research (e.g., Riedl et al. 2010a), related research models (e.g., Vom Brocke et al. 2013), or the design of a new IS artifact (e.g., Adam et al. 2016).

• Reviews: Articles in this category focus on the analysis of previous research, based on a review of the literature.

**Which major thematic orientation was chosen by NeuroIS researchers?**

Based on the information provided in the title and abstract, we classified each completed empirical paper (N = 103) into one of the four categories described in Dimoka et al. (2011, p. 691):

- Cognitive processes: all processes related to knowledge acquisition and understanding through experience and thought (e.g., cognitive effort),
- Emotional processes: all processes related to experience of positive or negative affect (e.g., fear),
- Social processes: all processes related to interaction among humans (e.g., cooperation),
- Decision-making processes: all processes related to selection of a course of action among several possibilities (e.g., purchase decision in online shopping).

The classification was carried out by the first author and the second author of this paper who independently conducted the classification. In 25 out of 103 cases there was no consensus. To determine the inter-rater reliability we used Cohen’s Kappa coefficient (Cohen 1960). This value indicates the degree of consistency of coding between two persons, while the possibility of random match (pc=1/4×1/4) is already taken into account. According to Landis and Koch (1977) values for the Cohen’s Kappa coefficients are “substantial” between 0.61 and 0.80 and values above are “almost perfect”. The value of Cohen’s Kappa coefficient for the 103 classified completed empirical papers was 0.74 [po=1-(25/103) and pc=1/16; see Cohen 1960, p. 40, for further methodological details]. Thus, the result of the coding is highly reliable.

It is important to note that even though the four categories constitute high-level topical abstractions, they are not mutually exclusive. It follows that some studies reference more than one category; yet, each paper has a primary focus on one of the four categories. For example, Javor et al. (2016) explored Parkinson patients’ (PD) trust in avatars; PD is a neurodegenerative disease that affects the motor system and cognitive and behavioral functions. Specifically, as outlined in detail in Javor et al. (2016), cognitive disturbances include deficits in domains such as attention and memory. Thus, this research domain is, at least at a first glance, closely related to both cognitive processes (deficits in cognition) and social processes (trust). However, because this investigation focuses on trust, and not on cognition and cognitive deficits, we classified this paper into the category “social processes”, and not into “cognitive processes”.

Dimoka et al. (2011, p. 690) write that the “proposed categorization simply aims to capture the breadth of mental processes that may be of interest to IS researchers”. Importantly, this primary focus of a paper became the decisive factor for determining classification. In the 25 cases in which the independent coding resulted in diverging classifications, the first author and second author discussed their perspectives and ultimately achieved agreement through this communication process. Finally, despite the fact that we are not aware of a formal measure to demonstrate that the four categories are collectively exhaustive, the relative abstract nature of the categories led to the situation that it was possible to categorize all 103 completed empirical papers based on the conceptualization by Dimoka et al. (2011). Thus, the conceptualization turned out as useful in our research context, confirming prior reports on the conceptualization’s usefulness to classify empirical NeuroIS papers (see Riedl and Léger 2016, p. 78).

**How was the empirical NeuroIS research conducted?**

We documented for each completed empirical paper the following methodological aspects:

- The tool which was used to collect neurophysiological data (e.g., fMRI, EEG, EDA, eyetracking).
- Setting of a study: We classified whether an empirical study collected data in a controlled environment (i.e., in the laboratory) or in a context that is natural to the study population (i.e., in the field). Importantly, although some studies simulated a natural setting within a controlled environment (e.g.,
Nunamaker et al. 2016; Ortiz de Guinea and Webster 2013b), we classified them as laboratory studies. An example for a field study is Fadel et al. 2015.

- Time scale: We classified whether data collection was longitudinal (at least two measurement points) or cross-sectional (one measurement point). Most of the reviewed studies applied neurophysiological measurement tools that collect data continuously (e.g., cardiovascular activity, electrodermal activity, or viewing patterns in eyetracking research). Hence, they formally fulfill the requirement of collecting data at more than one point in time. However, we only classified studies as longitudinal if time was of actual relevance in the context of the research topic. For example, we classified Bailey and Iqbal (2008) as longitudinal as they investigated the ideal timing of task interruptions (based on pupil dilation as a measure of mental workload), or Anderson et al. (2016b) as they investigated habituation effects related to the repeated viewing of security warnings.

- Country of investigation: We documented the countries in which data was collected, if reported. If not explicitly reported, and if all authors were affiliated with the same organization, or at least situated in the same country, we assumed, for student samples, that this country was also the country where the study took place. If individuals from a population other than students were recruited (e.g., professionals) and if authors were not from the same country, we classified that the country information was not available.

- Sample size: Indicates how many individuals participated in the study and also (if applicable) highlights in which part of the study they participated. In some cases more than one study is reported in one publication with different sample sizes (e.g., Nunamaker et al. 2011), and in other cases different samples have been used for each type of collected neurophysiological data (e.g., Adam et al. 2012). Importantly, if participants had to be excluded from further analyses (which is not uncommon in neurophysiological research, e.g., due to head movement in fMRI research), then we documented the sample size which was actually used for data analysis (e.g., Riedl et al. 2014b).

- Gender distribution in the sample: Indicates the number of female and male participants.

- Age distribution in the sample: Indicates the age of the participants (either indicated as average age or as age range).

### Findings of the Literature Review

In this section, we present major findings of our literature review. We structure the presentation of findings along the four research questions.

#### Who published NeuroIS research?

Based on the analysis of N = 164 NeuroIS publications, we identified 362 different authors. The average number of authors per publication is 3.45, and the maximum number of authors is 15. Specifically, we found the following results: 18 papers had 1 author (abbreviated: 1P/1A), 38P/2A, 44P/3A, 27P/4A, 22P/5A, 4P/6A, 6P/7A, 2P/8A, 0P/9A, 0P/10A, 1P/11A, 0P/12A, 0P/13A, 1P/14A, 1P/15A.

Another finding of our analysis is that out of the 362 different authors, 36 researchers (~10%) authored more than two publications. It follows that approximately 90% of the total number of authors published less than one paper every four years. At least one paper per year, on average across the analysis period 2008-2016, was published by three scholars (René Riedl: 21P, Pierre-Majorique Léger: 14P, Marc Adam: 9P).

Figure 1 shows the concentration of NeuroIS publications across authors. Based on our dataset, we calculated the Gini coefficient (GC), a popular measure of inequality. GC is 0.32, whereat GC=0 expresses perfect equality, where all authors would have contributed an equal number of publications to the NeuroIS literature, and GC=1 expresses maximal inequality. As shown on the right side in Figure 1, the top-36 contributors in NeuroIS research (based on number of published articles), who constitute approximately 10% of the total author population (the top-10.0% quantile), are responsible for 35% of all NeuroIS publications. Moreover, our results indicate that the top-2.5% quantile of all researchers (i.e., from René Riedl to Anthony Vance, see Figure 1) is responsible for 16% of all NeuroIS publications, the top-5.0% quantile (to Thomas Tullis) is responsible for 25%, and the top-7.5% quantile (to David Gefen) is responsible for 30%.
We also analyzed the number of papers published in the Senior Scholar’s Basket of the AIS, as well as the authors of these papers. As shown in Figure 2 (left), a total of 27 NeuroIS papers were published in the Basket journals in the analysis period 2008–2016 (19 empirical papers, 6 methodological papers, and 2 conceptual papers). Moreover, it can be seen that three of the eight Basket journals have not yet published NeuroIS papers (ISJ, JIT, JSIS), while JMIS has published 11 papers, the highest number in the sample of Basket journals, and JAIS has published 7 papers.

Authors with more than one NeuroIS paper in the AIS Senior Scholar’s Basket journals:

4P: Angelika Dimoka, Fred Davis, Ana Ortiz de Guinea, René Riedl

3P: Bonnie Anderson, David Eargle, Peter Kenning, Brock Kirwan, Anthony Vance

2P: Marc Adam, Alan Dennis, Varun Grover, Pierre-Majorique Léger, Paul Pavlou, Ryad Titah, Jeffrey Jenkins, Jason Thatcher, Jan vom Brocke

Figure 2. Number of NeuroIS Papers in the Senior Scholar’s Basket of the AIS (2008-2016) and Authors.
However, when interpreting these numbers one has to consider that both JMIS and JAIS published NeuroIS special issues in 2014. The two top journals in the field, MISQ and ISR, have published 6 and 2 NeuroIS papers, respectively. Using the NeuroIS publications in the Basket journals as a basis, we also analyzed the most productive authors. As shown in Figure 2 (right), four scholars have authored 4 papers, five scholars have authored 3 papers, and nine scholars have authored 2 papers in Basket journals. Thus, there are 18 scholars who have published at least two papers in Basket journals.

**What kind of NeuroIS research was published?**

Our analysis revealed for the 164 NeuroIS publications the following results: 103 papers are completed empirical studies (63%), 23 papers are empirical studies in-progress (14%), 14 publications are conceptual papers (9%), 23 publications are methodological papers (14%), and one paper is a review (Riedl 2013, a review of the technostress literature with a focus on neurobiology). Figure 3 shows the development of the five publication types in the period 2008-2016. In essence, there is a trend towards increased absolute number of completed empirical studies (see the blue bar). Other results should be interpreted with caution due to the low absolute numbers. As an example, the Journal of the Association for Information Systems (Vol. 15, No. 10) published a NeuroIS special issue with a focus on research methodology in 2014. This explains the relatively high number of methodological papers (see the gray bar) in 2014.

![Figure 3. Development of NeuroIS Research in the period 2008-2016 (N = 164).](image)

**Which major thematic orientation was chosen by NeuroIS researchers?**

Based on the specific topics addressed by the 103 completed papers, a classification of papers was carried out using the 4-category taxonomy by Dimoka et al. (2011). We found that most of the 103 analyzed papers have a thematic focus on either cognitive processes (51 papers, 50%) or emotional processes (33 papers, 32%). Social processes (8 papers, 8%) and decision-making processes (11 papers, 10%) have been investigated less often. Cognition and emotion, however, are involved in both social and decision-making processes. It follows that our findings indicate that the NeuroIS community has thus far investigated mainly the two fundamental processes, and has not yet fully examined their application with respect to social and decision-making processes.
How was the empirical NeuroIS research conducted?

Based on the sample of N = 103 papers, Figure 4 shows that eyetracking is the dominant tool in NeuroIS research (applied in 53 papers, 51%), followed by EEG (22 papers, 21%), measurement of heart rate (14 papers, 14%), and measurement of skin conductance (13 papers, 13%). fMRI has an adoption rate of 9% (9 papers), followed by functional electromyography (fEMG) (5 papers, 5%), measurement of hormones (5 papers, 5%), and blood pressure measurement (2 papers, 2%). Tools used in only one paper (part of Miscellaneous in Figure 4) are, for instance, vocal pitch measurement and diffusion tensor imaging. Figure 4 (left) shows the adoption rate of tools in NeuroIS research based on absolute numbers; Figure 4 (right) shows application of tools across the analysis period 2008-2016 in tabular form. Because some publications (e.g., Adam et al. 2012, Léger et al. 2014a) used more than one tool, the sum across all values in Figure 4 is greater than 103.

Moreover, we found the following results with regard to research methodology:

- Setting of a study (N = 103): 101 studies were carried out in the laboratory and 2 studies in the field.
- Time scale (N = 103): 52 studies are cross-sectional and 51 studies are longitudinal in nature.
- Country of investigation (N = 88): Country information was not available in 15 publications. In the remaining 88 publications, we found that 83 studies collected data in one country, 3 studies in two countries, and 2 studies in three countries. Specifically, we found the following results (in parentheses we indicate the number of papers): USA (33), Germany (8), Taiwan (7), Austria (6), China (6), Spain (5), Canada (4), Australia (3), Israel (3), Turkey (3), Netherlands (2), UK (2), France (1), Italy (1), Japan (1), Romania (1), and Switzerland (1). One paper indicated EU as geographic region of data collection.
- Sample size (N = 110): We found an average sample size of 54 subjects (min: 5, max: 451, median: 36, SD: 56). Information on sample size was not available in one publication.
- Gender distribution in the sample (N = 80): Gender distribution information was not available for 31 studies. Based on the remaining 80 studies, we found an average share of females of 48% (three studies only recruited male subjects and one study drew upon a completely female sample). The total number of recruited subjects across the 80 studies was 2,198 females and 2,337 males.
- Age distribution in the sample (N = 75): Age distribution information was not available for 36 studies. 57 studies reported the average subject age, and based on this information we calculated an average subject age in NeuroIS research of 26 years. 45 studies reported the minimum and maximum age of participants (min: 17, max: 88). The median of age range across the 45 studies is 14 years (min: 2, max: 64).

Discussion and Implications for Future NeuroIS Research

In this section, we discuss major findings of our literature review and implications for future NeuroIS research. We structure the discussion of findings and their implications along the four research questions.
Who published NeuroIS research?

We found an average number of authors per NeuroIS publication of 3.45. As reference values, we also analyzed the average number of authors of all 2016 MIS Quarterly and 2016 Information Systems Research papers (we did not include editorials in our analysis): MISQ: N = 51 papers (2.98); ISR: N = 48 papers (3.10). These averages are statistically significantly different from 3.45 (MISQ: p=0.018, ISR: p=0.090; SPSS 24). Thus, Riedl and Léger's (2016) “Division of labor” statement is supported by our data (for details, see the Section “Literature Analysis”). For example, the work of Javor et al. (2016) signifies a collaboration of an IS researcher with medical scientists, and the work of Vance et al. (2014) of IS researchers with cognitive neuroscientists. We also analyzed the average number of authors of four randomly selected 2016 issues (out of a total of 50 issues) of the Journal of Neuroscience (this is a leading journal in neuroscience research; selected issues: 4, 17, 30, 43; editorials were excluded from analysis): N = 96 papers (5.65). This average number is statistically significantly different from 3.45 (NeuroIS papers), 2.98 (MISQ), and 3.10 (ISR) (all three p-values are 0.000). Overall, these findings could indicate that research collaboration in NeuroIS is not yet fully reflected in a division of labor and co-authorships as observed in the neuroscience discipline. Yet, as our analysis shows, the average number of authors of NeuroIS papers is significantly higher than the average number of authors of non-NeuroIS papers (sample: 51 MISQ and 48 ISR papers).

We found that 362 different authors contributed to NeuroIS publications. Considering that NeuroIS exists for approximately one decade, we believe that this number is impressive. Also, we found that a share of 10% of all authors have published more than two papers in the period 2008-2016, and our findings indicate that these 10% published 35% of all NeuroIS papers. It follows that there is observable inequality in research contributions in the NeuroIS field. While we believe that it is impossible to observe no inequality in any research community, in the specific case of NeuroIS the small absolute number of highly engaged researchers, along with the observed inequality, can be viewed critical.

One major consequence of this inequality is that scholars who are potential candidates to act in the role of editors and reviewers for NeuroIS papers are relatively scarce (if compared to many other research fields in the IS discipline). However, our list of top-36 contributors in NeuroIS research (see Figure 1), or the short list of 18 scholars who have published at least two papers in Basket journals, can be used as a decision basis by editors-in-chief and senior editors of IS journals to select associate editors and reviewers. We emphasize that scholars who are not among the top-36, or top-18, contributors may also appropriately handle NeuroIS submissions. Yet, because journal and conference proceedings publications are the “currency of science” in a peer-review system, we argue that the NeuroIS scholars who contributed more significantly to the NeuroIS literature than other scholars, and in particular those who published NeuroIS papers in the Basket journals, are more successfully engaged in this type of research and hence are more likely to handle NeuroIS submissions in a high-quality way, either as editor or reviewer.

The finding that 90% of all authors have published not more than two papers in the period 2008-2016 can be viewed critical too. Because the planning and execution of high-quality NeuroIS studies requires significant knowledge, time resources, and, at least in some cases, considerable infrastructure investments (e.g., fMRI or high-quality EEG; Dimoka et al. 2012) along with software investments (e.g., to synchronize data; Riedl and Léger 2016), casual engagement in NeuroIS research, while principally possible, should be viewed skeptical (at least, if high-caliber research is the goal). The mentioned factors, therefore, seem to create an entry barrier that may, at least to some degree, prevent new scholars from entering the NeuroIS field. However, when interpreting this result, readers should consider that it is possible that some papers spent, and still spend, a very long time in journal review processes (given the novelty of the field and the resulting difficulty in finding qualified reviewers). Moreover, it is possible that some scholars “tested the waters”, and others still do, before focusing their full research attention on NeuroIS.

It is possible that a share of the 90% population who has published not more than two papers in the period 2008-2016 is currently overcoming the entry barrier and hence will become more engaged in NeuroIS research in the future. Note that this statement refers to the NeuroIS field as a whole, and one must not conclude that single authors who do not appear in the list of top-36 contributors (see Figure 1) are per se less productive authors or less engaged in NeuroIS activities. First, it is possible that an IS researcher has only recently decided to get engaged in NeuroIS, and hence it is hardly possible that such scholars have produced an equal number of publications if compared to the “pioneers” (i.e., scholars who started NeuroIS research quickly after its inception). Second, one must consider that established IS
scholars frequently carry out valuable editorial work at IS top journals, and hence their role in NeuroIS research is often predominantly the senior editor role rather than the author role. For example, David Gefen and Paul Pavlou (see Figure 1) have handled NeuroIS submissions in their role as senior editors of MIS Quarterly (e.g., Dimoka 2010, Riedl et al. 2010b, Vance et al. forthcoming).

What kind of NeuroIS research was published?

As indicated in Figure 3, we found a trend towards increased absolute number of completed empirical research in the NeuroIS field. While we identified only 26 completed empirical studies in the first five years of our investigation period (2008-2012), in 2016, the last year of our investigation period, we already identified 27 completed empirical studies. Considering that an increasing share of completed empirical studies indicates an increased maturity level, we conclude that the NeuroIS field has shown observable advancement.

In this review, we analyzed 66 outlets (55 peer-reviewed journals and 11 peer-reviewed conference proceedings) over the entire existence period of the NeuroIS field. Considering this large sample, we are confident that our review comprises a good deal of the worldwide available NeuroIS literature. It follows that one could argue that the 27 identified completed empirical studies in 2016, based on analysis of 66 outlets, is not much. Against this background, we conclude that while we observe an increasing maturity level in the NeuroIS field, the field is still in a relatively nascent stage. Moreover, Figure 2 (left) indicates the number of NeuroIS papers published in the Basket journals. Despite the exceptional situation in 2014 (two NeuroIS special issues appeared in this year), the number of NeuroIS papers published in the Basket journals is relatively low (2008: 0P, 2009: 1P, 2010: 2P, 2011: 2P, 2012: 2P, 2013: 2P, 2014: 10P, 2015: 4P, 2016: 4P). This fact further substantiates the conclusion that NeuroIS is still in a relatively nascent stage.

A notable finding of our review is the identification of 23 methodological papers (14% of the entire NeuroIS literature), 6 of which are published in Basket journals—MISQ: 1P, JMIS: 1P, JAIS: 4P (special issue with a focus on NeuroIS methodology). Example papers of this category are Dimoka’s (2012) fMRI guidelines, a paper on EEG as a research tool in the IS discipline by Müller-Putz et al. (2015), and an article by Gefen et al. (2014) that explains how functional near infrared (fNIR) spectroscopy can enhance IS research. We interpret this relatively high share of methodological papers as a good sign for the future development of the NeuroIS field, because this share indicates that NeuroIS scholars are well aware of the necessity to become familiar with the methods, tools, and measurements that are used in neuroscience and their idiosyncrasies if they are applied in IS contexts. As outlined by Riedl et al. (2014a), “[b]ased on a higher degree of familiarity [with the methods, tools, and measurements], IS academics (editors, reviewers, and authors) can develop sound methodological knowledge that is necessary to evaluate whether or not a specific method, tool, or measurement is suitable to study a specific IS research question and whether a method or tool is correctly applied. Without such a knowledge base, IS scholars cannot leverage the full potential of neuroscience for IS research because the production of scientific knowledge depends to a great extent on the techniques for collecting, analyzing, and interpreting data and the ways in which the techniques are applied” (p. ii). Considering the rationale of this statement, it is hoped that methodological contributions will stay important in future NeuroIS research. We foresee that methodological papers will shift from more general methods introductions (e.g., Dimoka 2012, Müller-Putz et al. 2015, Gefen et al. 2014) to more specific themes, such as analysis techniques for specific types of neuroscience data (e.g., Hubert et al. 2017).

Which major thematic orientation was chosen by NeuroIS researchers?

Our results indicate that most of the 103 completed empirical papers have a thematic focus on either cognitive processes (50%) or emotional processes (32%). Social processes (8%) and decision-making processes (10%) have been examined less often. Cognition and emotion are two fundamental processes, which are necessary components in social processes (e.g., computer-mediated interaction of people) and decision-making processes (e.g., purchase decision in an online shop). Hence, NeuroIS researchers have predominantly examined only the two fundamental processes, and have hardly studied their application in social and decision-making contexts. Considering that in the last two decades both social neuroscience (e.g., Cacioppo and Decety 2011) and decision neuroscience (e.g., Sanfey 2007) have developed significant insights into the neurobiology and behavior in social situations, as well as in decision-making situations, a
notable literature basis is available for NeuroIS research. Importantly, because cognition, emotion, human social interaction, and decision-making are all fundamental aspects in the study of the development, adoption, and impact of information and communication technologies (on various analytical levels, including individual, group, organization, and society), a more balanced investigation of these four processes would be desirable in future NeuroIS research.

With respect to the fact that social processes (8%) and decision-making processes (10%) make up less than 1/5 of the published NeuroIS research, we make a call for more future studies in these two important domains. Analyses of the IS literature (e.g., Sidorova et al. 2008, Steininger et al. 2009) reveal that trust is a central topic in IS research. Because disciplines such as neuroeconomics, social neuroscience, and consumer neuroscience identified trust several years ago as one of the most promising topics for exploration by means of neuroscience (e.g., Fehr and Camerer 2007), a rich body of knowledge on the neurobiological mechanisms underlying human trust behavior does exist (for a review, see Riedl and Javor 2012). IS researchers should use these existing literatures to advance IS theorizing. Importantly, several NeuroIS contributions already exist in this research domain (e.g., Dimoka et al. 2010, Riedl et al. 2010b, 2017), and these papers may serve as a conceptual and empirical basis for future NeuroIS studies. In addition to trust, several other social processes deserve attention in future NeuroIS studies, such as human interaction on social networking sites, developer-user interaction in software engineering, or computer-mediated communication.

In addition to investigation of social processes, exploration of decision-making processes should also become a more central topic in the future. Firstly, important IS topics such as decision support systems, artificial intelligence, and big data are closely related to decision making. Secondly, specialized literature exists on the foundations and applications of the neurobiology underlying human decision making (e.g., Dreher and Tremblay 2016). Thirdly, in our review we identified interesting empirical studies, which may serve as a foundation for future NeuroIS research on decision-making processes. For example, Zhou et al. (2015) explored decision making with galvanic skin response and pupillary analysis in the context of intelligent user interfaces; to state another example, Yang (2015) used eye-tracking to explore the Elaboration Likelihood Model (ELM) in online shopping. Considering these three facts, there is reason to assume that a good foundation exists that may support a rise of future NeuroIS research on decision-making processes.

With respect to the specific ratio of cognitive processes (50%, e.g., studies on mental workload in human-computer interaction) and emotional processes (32%, e.g., studies on arousal in online auctions), we believe that IS research would greatly benefit from an increasing number of NeuroIS studies on emotional processes. One of the major arguments for the use of neuroscience tools in IS research has been that such tools make possible the investigation of mental processes that are at least partly unconscious (such as “deep emotions”, Dimoka et al. 2011, p. 688). “Deep emotions”, as it has been argued in the extant literature (e.g., Dimoka et al. 2011, Riedl and Léger 2016, vom Brocke et al. 2013), are difficult to capture through survey instruments. It follows that NeuroIS research has to increase the number of studies on emotion in order to better meet the expectations regarding the contribution of neuroscience to IS research. An important publication, in this context, is Gregor et al.’s (2014) NeuroIS paper on emotions in IS research. In essence, this study develops a nomological network, including three interacting emotion systems: language, physiology, and behavior. Two experiments demonstrated the value of this nomological network. Gregor and colleagues (2014, p. 13) describe the contribution of their study as follows: “This research is novel and significant because it is possibly the first in-depth study to link the study of emotions in IS with a sound theory base and multiple measurement approaches, including neuroscience measures. It shows that an EEG measure has some predictive power for an outcome such as e-loyality.”

This call for more NeuroIS research with a direct focus on emotional processes is substantiated by the fact that the influence of emotions on important IS outcome variables has become an established fact in IS discipline in the last two decades. For example, evidence indicates that emotion (conceptualized as computer anxiety) is an important determinant of perceived ease of use (Venkatesh 2000). Moreover, further evidence shows that a person’s emotion influences the willingness to disclose personal health information (Anderson and Agarwal 2011). Considering this increasing importance of emotion in various IS research domains, the use of neurophysiological measurement instruments promises to deliver new insights, because neurophysiological data can explain variance in important IS outcome variables that cannot be explained by survey data alone (e.g., Tams et al. 2014). An increasing trend towards more
studies on emotion in future NeuroIS research is promoted by the fact that several relatively inexpensive and unobtrusive tools exist that can be used to capture emotions, such as heart rate or skin conductance measurement.


dow was the empirical NeuroIS research conducted?

d this review revealed that eyetracking is the dominant tool in NeuroIS research (51% of the completed empirical studies used this tool), followed by EEG (21%), heart rate measurement (14%), skin conductance measurement (13%), fMRI (9%), fEMG (5%), hormone measurement (5%), and blood pressure measurement (2%). note that because some studies such as Adam et al. (2012) or Léger et al. (2014) used more than one tool, the sum across all values is greater than 100%.

Based on this finding, we conclude that NeuroIS research thus far has studied activity of the autonomic nervous system (pupil dilation, heart rate, skin conductance, fEMG, blood pressure) more frequently than actual brain activity (EEG, fMRI). We surmise that this state is mainly a consequence of access to research facilities and costs of instruments. In essence, acquisition of instruments related to autonomic nervous system activity is typically cheaper than acquisition of brain measurement tools. For example, acquisition of heart rate or skin conductance measurement tools is possible for a few thousands US$, sometimes even cheaper, while the acquisition of a high-quality EEG system may cost 50,000 US$, sometimes even more, and acquisition of an MRI machine may cost 1.5-3.0 million US$.

Another potential reason for our finding is intrusiveness, indicating “the extent to which a measurement instrument interferes with an ongoing task, which thereby distorts the investigated construct”, and which is influenced by (i) degree of movement freedom (“indicates whether a person is able to move during task execution”), degree of natural position (“indicates whether a person is able to carry out a task in a natural position”), and degree of invasiveness (“the extent to which the recording device of a measurement instrument has to be inserted into or attached to the body”) (Riedl et al. 2014a, pp. xxvi-xxviii). Obviously, lying still on ones back in a MRI machine implies a high degree of intrusiveness, if compared to eyetracking, heart rate recording, or skin conductance measurement. Thus, our findings suggest that high ecological validity (that is typically achieved in eyetracking research and some other methods related to measurement of autonomic nervous system activity) is a major objective in NeuroIS research.

With respect to EEG, we found that some papers used instruments which were not developed for research purposes. In the last decade, companies with a primary focus on video gaming developed relatively cheap EEG-based headsets for players to control the game (e.g., Emotiv EPOC, a 14 channel wireless EEG headset). Importantly, such EEG systems differ from established EEG research tools (e.g., Neuroscan). In our review we identified 22 completed empirical EEG studies, of which 11 studies used Emotiv EPOC. Other tools which were used less frequently are B-Alert X10 (4 studies), NeuroSky mindset headset (1 study) and MUSE brain sensing headband (1 study). It is beyond the scope of the present review paper to discuss this issue in detail. However, this finding is an observation that deserves closer attention in future methodological papers. In essence, while validation studies exist which suggest that the use of tools like Emotiv EPOC is adequate for academic research purposes (e.g., Lissa et al. 2015), other studies are more skeptical. Duvinage et al. (2013) write that “the Emotiv headset performs significantly worse than the [ANT system, Advanced Neuro Technology]” (p. 1). Based on this finding, Duvinage et al. (2013) recommend that Emotiv should only be used “for non critical applications such as games, communication systems, etc.” (p. 1). Academic NeuroIS research is certainly not a “non critical application”. Thus, as long as the reliability and validity of these non-research EEG instruments have not been established undoubtedly, in our opinion such systems should not be used in NeuroIS research, at least if the research is intended to be published in a high-quality journal. We are not aware of EEG research based on instruments which were primarily developed for video gaming purposes that is published in high-impact cognitive neuroscience journals. We make a call for future methodological studies that compare, based on IS research contexts, the differences and similarities of EEG-based headsets from the gaming industry and EEG instruments that were developed for academic research purposes.

Another striking result related to NeuroIS methodology is that 101 studies (of completed research) were carried out in the laboratory, while only 2 studies were conducted in field settings (Caya et al. 2012; Fadel et al. 2015). A major reason of this imbalance is a false belief that seems to persist in the NeuroIS field since its genesis in 2007, namely that NeuroIS research has a sole focus on the individual level of analysis, and because research on this level of analysis is frequently conducted based on the laboratory experiment
as research method, the fact that almost 100% of empirical NeuroIS research was carried out in the laboratory is not surprising for people adept in NeuroIS. Another reason is that running studies in a controlled laboratory environment is usually less effortful and less risky (with respect to research results expectations) if compared to field studies.

Tools related to the measurement of autonomic nervous system activity, several of which can be applied in field settings (e.g., in offices), play a significant role in NeuroIS research (Dimoka et al. 2012). Against this background, we argue that more NeuroIS research should be carried out in field settings, in particular because this kind of research can also inform research questions on the organizational level of analysis. This call for more field research is important because prior studies have shown that the organizational level of analysis is the dominant one in IS research (e.g., Vessey et al. 2002). It follows that if NeuroIS was only relevant for research on the individual level of analysis, its potential for IS research would be limited. In the only review paper that we could identify in our sample of 164 NeuroIS publications, Riedl (2013) discusses a number of field studies that examined technostress, based on neurophysiological tools, in field settings. Future research should identify further IS topics which are suitable for investigation by means of neuroscience approaches in field settings.

In this context, Fischer and Riedl (2016) recently presented the idea to use lifelogging data for NeuroIS research purposes. Lifelogging has the objective of enabling an individual to collect the totality of his/her experiences through the digitization of all cognitive inputs and/or neurophysiological activation (Dodge and Kitchin 2007). With respect to neurophysiological activation, recent evidence indicates that heart rate responses are unique for conscious emotions and implicit emotions that cannot be consciously experienced (Ivonin et al. 2013). Because heart rate is increasingly measured by people, based on unobtrusive and low-cost smartwatches, and because this data can be provided by individuals for research purposes, the increasing trend towards lifelogging promises to deliver new research opportunities for NeuroIS scholars. Similar applications are known based on other physiological signals, such as skin conductance (for a technology available in practice, see, for example, https://www.empatica.com/). However, considering the calls for application of high methodological standards in NeuroIS research (e.g., Riedl et al. 2014a), reliability and validity of measurement instruments must not be traded-off against easy data access opportunities through lifelogging. It follows that a vital field of study in future NeuroIS research is the investigation of the reliability and validity of smartwatches, fitness-trackers, and smartphones in combination with specific apps that are able to capture and analyze neurophysiological signals.

With respect to our results on country of investigation (a striking dominance of North America, data on country was available in 88 studies), gender distribution in the sample (average share of females of 48%, reported in 80 studies), and age distribution in the sample (average age of 26 years, reported in 57 studies; median of age range of 14 years, reported in 45 studies), it is critical to reflect these results in the light of neuroscience evidence showing that culture, gender, and age are important moderator variables (see Appendix C in Dimoka et al. 2012, where some key findings and their implications for IS research are reviewed). Importantly, the fact that not every single completed empirical study did report the geographic area of data collection, as well as gender and age distribution in the sample, is problematic itself. Moreover, we make a call for more direct investigations into the role of culture, gender, and age in IS research based on neurophysiological tools and/or neuroscience theories. A few example papers are already available, such as Cyr et al.’s (2009) multi-method study (including eyetracking) on website design in three different cultures (Canada, Germany, Japan), Riedl et al.’s (2016b) fMRI study on gender differences in online trust, and Tams’ (2016) study on the question of why older workers are especially techno-stressed in environments that are characterized by frequent interruptions caused by technology use (stress was assessed biologically via salivary α-amylase).

With regard to time scale we found that 52 studies are cross-sectional, while 51 studies are longitudinal. Remember that we only classified studies as longitudinal if time was of actual relevance in the context of the research topic (e.g., Bailey and Iqbal 2008, Anderson et al. 2016b). Against this background, we interpret our finding that an almost equal number of NeuroIS studies is longitudinal in nature as a positive characteristic of NeuroIS research (for arguments why longitudinal research is of particular value in IS studies, see, for example, seminal papers by Vitalari 1985 and Venkatesh and Vitalari 1991). It is hoped that future NeuroIS studies will keep the explicit consideration of temporal aspects in the study of IS phenomena.
We found an average sample size of 54 subjects involved in the collection of neurophysiological data (min: 5, max: 451, median: 36, SD: 56). While this sample size is smaller than in traditional IS studies using survey and behavioral laboratory experiments as research methods, it is relatively large if compared to brain imaging studies. A review of papers, including studies in prestigious journals such as Neuron, Science, and Nature revealed that the average sample size is $N = 18$ in brain imaging studies (Lieberman et al. 2009, p. 301). However, one should not rashly conclude that NeuroIS studies, with regard to sample size, outperform top neuroscience research. One major explanation for this relatively large average sample size is that fMRI research is, at least currently, not a frequently used tool in the NeuroIS field (9% of completed empirical studies). In neuroscience, the situation is different—fMRI is the dominating tool (e.g., Logothetis 2008), and hence the relatively small average sample size of 18 subjects bears on the fact that a majority of neuroscience research published in top journals is based on fMRI, for which it is typical to have sample sizes between 15-25 subjects. Based on our review, we found that the average sample size of the 6 fMRI studies published in Basket journals is 20 subjects (Anderson et al. 2016, N=25; Dimoka 2010, N=15; Jenkins et al. 2016, N=24; Riedl et al. 2010b, N=20; Riedl et al. 2014b, N=18; Warkentin et al. 2016, N=17). It follows that the average sample size of fMRI research published in top IS journals is similar to the average sample size of top neuroscience research applying fMRI. Altogether, based on the findings of our review we have no reason to assume that low sample size is a pressing issue in the NeuroIS field. Rather, more pressing issues exist; in particular, the occasional use of “gadgets” to collect neuroscience data without an academically serious proof of the tool’s reliability and validity, or the hardly existing field studies. Table 3 summarizes the key findings of this study and implications for NeuroIS.

<table>
<thead>
<tr>
<th>Question</th>
<th>Key Finding (KF) and Implication (I)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Who published NeuroIS research?</td>
<td>KF: 362 different authors contributed to NeuroIS research, I: the NeuroIS field has reached a critical mass of researchers.</td>
</tr>
<tr>
<td>What kind of NeuroIS research was published?</td>
<td>KF: More and more completed empirical studies were published over the years, I: the NeuroIS field has shown obvious development and has reached a perceptible maturity level.</td>
</tr>
<tr>
<td>Which major thematic orientation was chosen by NeuroIS researchers?</td>
<td>KF: Cognitive processes and emotional processes were the dominant orientation, I: social processes and decision-making processes should be explored more intensively in the future.</td>
</tr>
<tr>
<td>How was the empirical NeuroIS research conducted?</td>
<td>KF: NeuroIS research studied activity of the autonomic nervous system (e.g., pupil dilation, heart rate, skin conductance) more frequently than actual brain activity (e.g., fMRI), I: this fact is not necessarily negative, because the intrusiveness of brain activity measurement tools is typically higher than the intrusiveness of autonomic nervous system measurement tools.</td>
</tr>
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Limitations and Concluding Statement

In the present investigation, we reviewed 164 NeuroIS papers published since the genesis of NeuroIS in December 2007. To the best of our knowledge, this review is the most comprehensive study of the NeuroIS literature that is currently available. Yet, the present review has limitations. First, the present study focused on IS journals and proceedings, as well as outlets from related fields (e.g., human-computer interaction). However, our review does not include studies published in outlets from neuroscience, psychology, and medicine. As an example, our review does not include a study by Small and colleagues (2009), published in the American Journal of Geriatric Psychiatry, which examined patterns of cerebral activation during Internet search. Thus, future examinations should extend the present review to other research disciplines. Second, while we consider our data collection and data analysis approaches as rigorous (see “Methodology of the Literature Review”), our interpretation of the findings (see “Discussion and Implications for Future NeuroIS Research”) is predominantly interpretive. Against the background of our results, in the present paper we argued that the NeuroIS field is still in a relatively nascent stage, despite its undeniable achievements. However, other scholars eventually draw different conclusions based on our findings, interpreting our results as more positive, or more negative, than we do. For example, one
might argue that some methodological challenges are frequently observed in emerging disciplines, and hence, while they should be taken into account in future studies, they should not hamper the prosperous long-term development of the NeuroIS field. NeuroIS has become an established research field in the IS discipline. Despite our finding that there is some inequality in research output, the NeuroIS community has definitely reached a critical mass of active researchers who serve in the role of author, reviewer, and editor. Moreover, the potential contributions of neuroscience to the IS literature are much clearer today (see, for example, Riedl and Léger 2016) if compared to the early years of the field. It follows that the expectations regarding the potential of NeuroIS to contribute to both IS theory and practice seems to be fairly realistic today. It is hoped that in the next decade the NeuroIS field will continue to make the same progress that it has made during the last ten years and that action, and that action will be taken to cope with the challenges that we identified in this review.

Appendix

In the following, we list all journals and proceedings which were analyzed in the present review. Abbreviations are based on Web of Science (for details please refer to: https://images.webofknowledge.com/WOK46P9/help/WOS/A_abrvjt.html, last access on April 19, 2017).


We did not analyze papers from the following sources because they do not focus on IS research, despite the fact that they are listed in the ranking of the German Academic Association for Business Research (VHB, for details, please see http://vhbonline.org/vhb4you/jourqual/vhb-jourqual-3/teilrating-wi/): ACM COMPUT REV, ACM COMPUT SURV, ARTIF INT, BIT BANKING INFORM TECHNOL, BUS PROCESS MGMT J, COMPUT OPER RES, COMPUT IND, DATA KNOWL ENG, E-SERVICE J, GROUP DECIS NEGOT, HMD, IEEE COMPUTER, IEEE SOFTWARE, IEEE T ENG MANAGE, IEEE T SOFTWARE ENG, INFORMATIK-SPEKTRUM, INFORMS J COMPUT, INT J MEDIA MGMT, INT J SERV SCI MGMT ENG TECH, J COMPUT FINANC, LECT NOTES COMPUT SC, LECT NOTES INFORMAT, MATH PROGRAM, SIAM J COMPUT, TELECOMMUN POLICY.

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References

Papers with an asterisk indicate the 164 publications which were reviewed in the present article.


A Decade of NeuroIS Research


A Decade of NeuroIS Research


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