APPLICATION STRATEGIES FOR NEUROSCIENCE IN INFORMATION SYSTEMS DESIGN SCIENCE RESEARCH

JAN VOM BROCKE
University of Liechtenstein
Vaduz, Liechtenstein

RENÉ RIEDL
University of Linz
Linz, Austria

PIERRE-MAJORIQUE LÉGER
HEC Montréal
Montréal, Canada

ABSTRACT

Design science has evolved as a major research paradigm in the information systems (IS) discipline, which aims to design innovative and useful IT artifacts, such as conceptual models and software systems. Despite the increasing attention paid to the cognitive and emotional mechanisms that underlie the perception of such artifacts, research that explores the neurobiological determinants of these mechanisms has only recently begun to emerge. The primary argument for the use of neurobiological approaches in IS design science research is that IT artifact design — and, ultimately, human-computer interaction in general — may significantly benefit from neuroscience theories, concepts, methods, and data. In particular, the consideration of neuroscience may improve IT artifacts' alignment with users' perceptual and information processing mechanisms, particularly the brain. Against this background, this article presents a taxonomy of application strategies for neuroscience in IS design science research. It describes three major areas of application and explains that conducting research in an area comes with a specific set of requirements (e.g., applicability, costs, accessibility, and knowledge relevant to planning and conducting a research project). Therefore, if an IS design science scholar decides to draw upon neuroscience, the taxonomy transparently explains possible working areas and corresponding requirements. The taxonomy is described based on example studies published in the IS literature and on contributions that appeared in outlets pertaining to related disciplines, such as affective computing and neuroergonomics. The article concludes that, if neuroscience is considered a valuable complement to the more traditional approaches, it has the potential to become a major reference discipline for IS design science research.

KEYWORDS: Design science research, Neuroscience, fMRI, EEG, Affective computing, Neuroergonomics.

1. INTRODUCTION

Design science research in the information systems (IS) discipline investigates the design process of IT artifacts (e.g., conceptual models and software systems) and the output of this process, that is, the artifact itself [34, 46, 58]. This research paradigm has received significant attention in the IS literature during the most recent decade [e.g., 32, 34]. However, design science research is still an emerging field in information systems and studies pertaining to this paradigm are important [82]. In addition, both the design of IT artifacts and corresponding meta-research are indispensable to an applied science like IS because technological artifacts "lend utility to theory" [9, p. 271]. The DESRIST conference (design science research in information systems and technology) is an annual event to discuss design science research as an emerging paradigm in IS research [84].

The design of an IT artifact is associated with a number of questions related to human perception and information processing. With respect to conceptual models, for example [5, 10, 50], two questions, among others, are relevant: Which modeling language is suitable? How can the comprehensibility of a model be guaranteed? Clearly, posing these and similar questions signifies a user-centered, rather than a technology-centered, perspective. In fact, recent studies in the field of conceptual modeling have called for a focus on user perception and information processing, thereby putting the user, as a human being, and not the artifact at the center of interest [49, 62]. Another prominent type of artifact is software system design, and research in various domains of this field has called for a focus on the human element. Examples can be found in requirements engineering [e.g., 70, 76], usability engineering [e.g., 35, 52], and human-computer interaction [e.g., 16, 26].

Engineering initiatives in disciplines like affective computing [59] and neuroergonomics [55] have shown that the bio-signals that indicate a user's emotional and affective state (e.g., facial expressions, pupil dilation, skin conductance, brain waves) may be automatically monitored by a system so it can dynamically adapt the user interface to the user's state. For example, a system may use eye-tracking technology to recognize that a user is stressed (dilated pupils) and adjust the interface in real-time to reduce the user's perceived level of stress [89] by, for example, reducing the amount of information presented on the screen or by changing the information presentation mode from textual to spatial. It has been argued that such "intelligent systems" may increase a user's sense of well being, thereby positively affecting performance and productivity in human-computer interaction [56, 60].

Considering these developments in research and engineering, we observe a current trend in IS research toward neuroscience's becoming a reference discipline for the IS field. A new discipline, NeuroIS, an interdisciplinary field of research that merges the disciplines of IS and neuroscience, has developed. Dimoka et al. [21] define NeuroIS as the "idea of applying cognitive neuroscience theories, methods, and tools in Information Systems (IS) research." During the past five years, a number of conceptual and empirical NeuroIS papers have been published (see, e.g., [87]). However, the consideration of neuroscience is still in its infancy in IS design science research. A limited number of contributions have alluded to the potential of neuroscience in design science research [e.g., 42, 80], but few IS design science studies have applied neuroscience theories and tools, perhaps because of a lack of conceptual support for IS researchers who wish to engage in NeuroIS design science research.

In particular, despite the valuable insights already available in the NeuroIS field, a taxonomy of application strategies for neuroscience in IS design research has not yet been presented. The objective of this article is to develop such a taxonomy. By this, we intend to support IS researchers in applying neuroscience theories and tools in design science research . . . (DSR). The taxonomy is derived from both the DSR and NeuroIS literature and it is subsequently described based on example studies published in the cognitive neuroscience literature. Also, we consider contributions that have appeared in outlets pertaining to related disciplines such as affective computing, brain-computer interaction, and neuroergonomics. Therefore, although this article is geared to IS scholars, academics in computer science, engineering, psychology, neuroscience, and other fields may also benefit from the taxonomy. We hope that the taxonomy leads to improved understanding of the potential of neuroscience for IS design science and that it helps to identify avenues for future research and development projects in practice. Our taxonomy also identifies the requirements associated with specific types of neuroscience-based design science research (e.g., applicability, costs, accessibility, and knowledge relevant to planning and conducting a research project). This will help design science scholars decide whether to engage in NeuroIS at all, and if so, which specific working area to choose.

The remainder of this article is structured as follows: Section 2 describes neuroscience and design science in the context of IS research. Then section 3 discusses three application strategies for neuroscience in IS design science research and presents example studies from cognitive neuroscience, affective computing, brain-computer interaction, and neuroergonomics. Section 4 explains how each application strategy is associated with a specific set of requirements (e.g., neuroscience knowledge, budget) and compares the three strategies based on the requirements so IS design science scholars are transparently informed about the implications associated with engaging in one application area or the other. Finally, section 5 concludes.

2. NEUROSCIENCE AND DESIGN SCIENCE IN THE CONTEXT OF IS RESEARCH

Before we present our taxonomy in the next section, we begin with brief explanations of neuroscience and design science in the context of IS research in order to create a conceptual basis for the subsequent sections.

2.1 Neuroscience and IS

The role of neuroscience in IS research has been studied in the field of NeuroIS [18, 21, 63]. A group of fifteen IS researchers and academics from other disciplines with strong backgrounds in the brain sciences (e.g., neuropsychologists and neuroeconomists) recently developed a comprehensive definition for this concept:

> "NeuroIS is a subfield in the IS literature that relies on neuroscience and neurophysiological theories and tools to better understand the development, use, and impact of information technologies (IT). NeuroIS seeks to contribute to (i) the development of new theories that make possible accurate predictions of IT-related behaviors, and (ii) the design of IT artifacts that positively affect economic and non-economic variables (e.g., productivity, satisfaction, adoption, well being)." [63, p. 245]

This definition makes evident four major characteristics of NeuroIS. First, neuroscience and neurophysiology are both considered integral parts of NeuroIS, so the central nervous system, of which the brain is the major part, is of interest, but so are other biological systems, such as the autonomic and somatic nervous system (with subcomponents like the electrodermal and cardiovascular systems), the face (with its muscles), and the eyes. The second major characteristic of NeuroIS is that NeuroIS does not necessarily require the use of neuroscience tools like functional magnetic resonance imaging (fMRI) or electroencephalography (EEG) but may include the development of arguments or hypotheses based on neuroscience theories. Third, NeuroIS is comprised of both theoretical research (in terms of cause-effect relationships) and the design of IT artifacts. Finally, in contrast to "pure" neuroscience, NeuroIS seeks to investigate the relationship between neural and behavioral mechanisms and so assumes that neural and neurophysiological activity precedes behavior [13]. All together, then, NeuroIS seeks to develop neurobiologically grounded theories (based on genetics, endocrinology, brain imaging, and neurophysiology; [e.g., 65]) that help explain IT behavior and develop innovative and useful IT artifacts.

2.2 Design Science and IS

Significant contributions to design science research in IS were published in the early 1990s. A major contribution made Simon [73] with his book "The Science of the Artificial." In a seminal paper, Walls et al. [81, p. 36] presented an information systems design theory (ISDT) for executive information systems that describes a prescriptive theory, the ISDT, "which integrates normative and descriptive theories into design paths intended to produce more effective information systems." Later, March and Smith published an essay in which they argued that "both design science and natural science activities are needed to ensure that IT research is both relevant and effective" [46, p. 251]. Thus, this article argued for a "dual perspective" in IS research that embraced the complementary nature of theoretical research and design science. It discusses that theories can be used to develop IT artifacts that serve a specific purpose and that are referred to as "technological rules" that take the form: "If you want to achieve Y in situation Z, then something like action [design] X will help" [77, p. 227].

In the 2000s, Hevner et al. [34] renewed the call for design science research in the IS discipline because "the IS field seemed not to echo with their work" to the seminal contributions published in the 1990s [82, p. 12]. The primary goal of Hevner et al. [34, p. 77] was to "inform the community of IS researchers and practitioners of how to conduct, evaluate, and present design science research." Another well-known paper [32] drew upon the work of Walls et al. [81] to present eight components of design theories, referred to as "The Anatomy of a Design Theory."

Considering the several special issues published on IS design science research (e.g., *MIS Quarterly*, Vol. 32, No. 4, 2008, *Information Systems and e-Business Management*, Vol. 9, No. 1, 2011), the increasing number of high-quality design science publications in the IS literature [e.g., 3, 57], and the design science background of an increasing number of editorial board members of mainstream IS journals in Europe and North America [8], as well as other regions, such as Asia and Australia, there is reason to assume that design science research has "arrived" throughout the IS discipline.

Despite the individual contributions that seminal papers [e.g., 81, 46, 34, 32] have made, the question remains concerning whether there are arguments or principles that are important in IS design science research in general. Although it is far beyond the scope of this article to present a comprehensive analysis of the similarities and differences in the papers' contributions and messages, at least two pivotal principles become evident across most papers.

Principle 1: Design decisions should be well justified and based on existing theoretical research.

For example, March and Smith discussed "justify" and "theorize" as research activities in their design science research framework, writing, "If significant progress is to be made, IT research must also develop an understanding of how and why IT systems work or do not work" [46, p. 251]. Similarly, Walls et al. ("kernel theories," [81, p. 44]), Hevner et al. ("truth informs design," [34, p. 80]), and Gregor and Jones ("justificatory knowledge," [32, p. 322]) argued in their frameworks for theory-based designs.

Principle 2: Once an IT artifact (e.g., software system) has been built, it should be evaluated.

March and Smith explained that "build" addresses the question, "Does it work?" and "evaluate" refers to "How well does it work?" They wrote, "Evaluation requires the development of metrics and the measurement of artifacts according to those metrics. Metrics are used to assess the performance of an artifact. Lack of metrics and failure to measure artifact performance according to established criteria result in an inability to effectively judge research efforts" [46, p. 258]. Walls et al. [81] and Gregor and Jones [32] also discussed evaluation as a research activity that tests whether pursued goals are accomplished. Finally, Hevner et al. [34, p. 83] defined the design-science research guideline, "Design Evaluation," and wrote, "The utility, quality, and efficacy of a design artifact must be rigorously demonstrated via well-executed evaluation methods."

3. A TAXONOMY OF APPLICATION STRATEGIES FOR NEUROSCIENCE IN IS DESIGN SCIENCE RESEARCH

Based on the discussion in the previous section, two conclusions can be drawn: (i) neuroscience offers both *theories* and *tools* for IS research and (ii) *build* and *evaluate* are major activities in IS design science research. Against this background, we derive a 2×2 matrix (Figure 1).

The framework illustrated in Figure 1 shows four fields for NeuroIS design science research: neuroscience theories can inform the building of IT artifacts, neuroscience theories can be used as a basis for the evaluation of artifacts, neuroscience tools (e.g., fMRI, EEG) can be applied to evaluate IT artifacts, and neuroscience tools can be used as a built-in function of an information system.

Against the background of the framework presented in Figure 1, three application strategies for neuroscience in IS design science research can be derived:

- **Strategy 1:** Use neuroscience theories to inform the building and evaluation of IT artifacts.
- **Strategy 2:** Use neuroscience tools to evaluate IT artifacts.
- **Strategy 3:** Use neuroscience tools as built-in functions of IT artifacts.

We integrate the use of neuroscience theories to build IT artifacts and as a basis for the evaluation of artifacts (Figure 1) into one field because the two uses are conceptually similar since the difference refers only to the time the theory is used since building precedes evaluation. In addition, a design process is usually iterative [e.g., 47], so design and evaluation activities are closely linked (even though their conceptual separation may be useful). Thus, three applications strategies result. We present examples for each application strategy in the following.

3.1 Application Strategy 1: Use of neuroscience theories to inform the building and evaluation of IT artifacts

Neuroscience theories are present in a number of research fields, including molecular and cellular neuroscience, developmental neuroscience, neural diseases (e.g., Alzheimer's or Parkinson's disease) and disorders (e.g., autism or schizophrenia), computational neuroscience (e.g., neural networks), and cognitive neuroscience. The last has been identified as a major reference discipline for the IS field. Dimoka et al. [18, p. 6] write:

> "IS researchers are advised to first become familiar with prominent cognitive neuroscience theories and more specifically with findings about the localization of various processes and constructs in the brain [. . .] . [T]he field of NeuroIS does not need to grow exclusively by conducting neuropsychological studies, which may be arguably perceived as a huge barrier due to the accessibility, cost, and steep learning curve associated with neuropsychological tools. There is a very rich literature in cognitive neuroscience [. . .] that IS researchers can draw upon to inform their theories and potentially stimulate traditional IS studies."

Cognitive neuroscience seeks to understand "how the brain works, how its structure and function affect behavior, and ultimately how the brain enables the mind" [29, p. 2]. Cognitive neuroscience theories may have different levels of abstraction: some theories may describe the functioning of the human brain on a relatively abstract level (e.g., X- and C-Systems Theory), while others may discuss the specific neural correlates of perceptual,

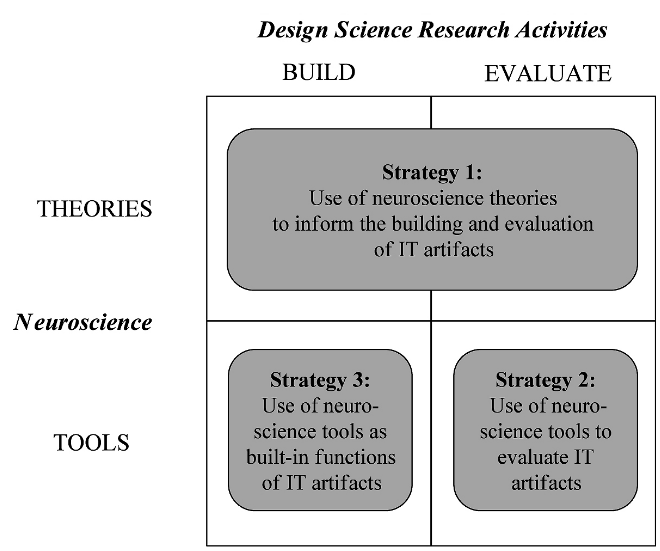

FIGURE 1. NeuroIS Design Science Research Framework

informational, or mental processes — that is, perception of or thoughts on *A* correlate with activity in brain region *B*. For example, the fusiform face area (FFA) is a part of the human brain that is specialized in face recognition.

Next we describe an abstract cognitive neuroscience theory (example 1) and a specific cognitive neuroscience theory (example 2) in order to demonstrate the potential neuroscience theories have for building and evaluating IT artifacts like software systems and conceptual models. Because of the theories' varying abstraction levels, the implications for IS design science theorizing imply varying degrees of specificity. In the case of the more abstract theory, the implications are more general in nature and a methodological implication is discussed, while in case of the specific theory, the implication for artifact building and evaluation is more specific.

Example 1: X- and C-Systems Theory

In psychology, the existence of two different modes of thinking and deciding that correspond roughly to the everyday concepts of intuition and reasoning was suggested several decades ago. (See, e.g., the literature cited in Kahneman [38].) This stream of research, which is referred to as dual-processing theories [74], hypothesizes that intuition is associative, holistic, automatic, relatively undemanding of cognitive capacity, relatively fast, and often emotionally charged, whereas reasoning is rule-based, analytic, controlled, demanding of cognitive capacity, and relatively slow.

During the past decade, cognitive neuroscience researchers like Matthew D. Lieberman and colleagues have identified brain structures that correspond roughly to intuition and reasoning (Figure 2). In the notation of this theory, intuition is referred to as the X-System (refle<u>x</u>ive), while reasoning is referred to as the C-System (refle<u>c</u>tive).

This theory suggests that automatic processes in the X-System are more associated than are those in the C-System with activity in the orbitofrontal cortex (OFC), basal ganglia (BG), amygdala (A), lateral temporal cortex (LTC), and dorsal anterior cingulate cortex (dACC) (Figure 2). In contrast, controlled processes in the C-System are more related than are those in the X-System to activity in the lateral prefrontal cortex (LPFC), medial temporal lobe (MTL), posterior parietal cortex (PPC), rostral ACC, medial PFC, and dorsomedial PFC.

The theory argues that automatic processes are the background mode of brain functioning, so they are active most of the time. Only when automatic processes are interrupted (e.g., because of unexpected events, strong visceral states, or novel decision situations) do controlled processes become active. Moreover, the theory argues that the X-System and its corresponding brain structures are phylogenetically older than the C-System and its structures [43, 68]. Therefore, automatic processes, which are typically emotional in nature, are hypothesized to affect human behavior more than controlled processes do, . . . at least they influence behavior significantly more than most behavioral sciences have assumed.

The X- and C-Systems theory is important for IS design science research in general, and particularly for the building and evaluation of IT artifacts. Historically, technology acceptance theorizing has been significantly influenced by models from social psychology that emphasize conscious, deliberate judgment and decision making processes, such as the Theory of Reasoned Action (TRA) and the Theory of Planned Behavior (TPB) (e.g., Davis and Banker in Loos et al. [45]). However, the X- and C-Systems theory suggests that behavior is driven by two different systems and that the X-System often affects behavior more strongly than the C-System does [15, 43, 68]. Therefore, IS design science research should consider automatic and emotional processes much more than it

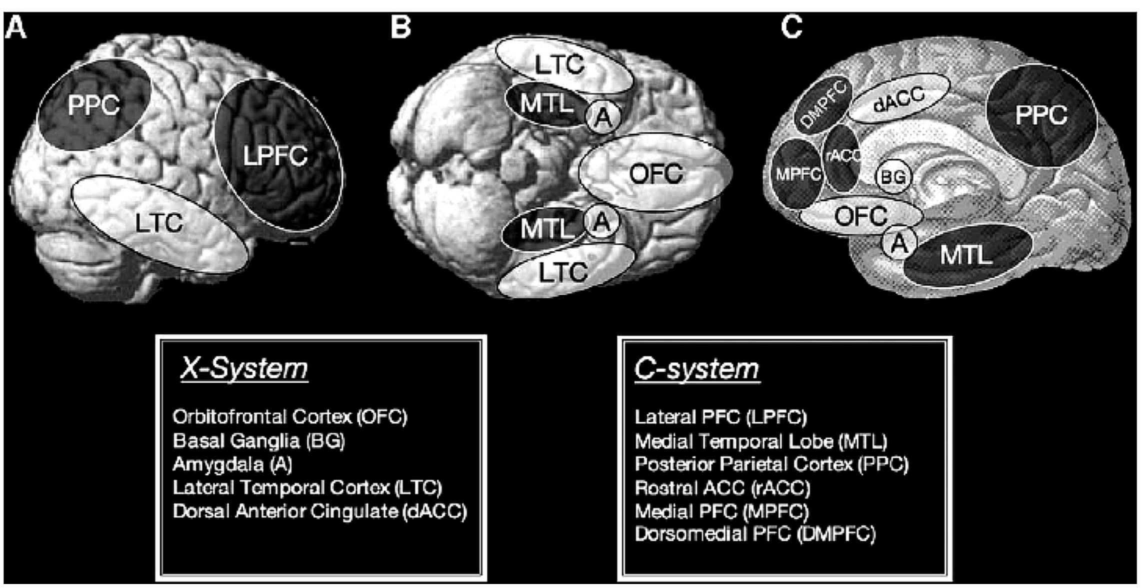

FIGURE 2. X- and C-Systems Brain Structures (Source: [68, p. 87])

Notes: The brain structures are displayed from the (A) lateral, (B) ventral, and (C) medial views. Some structures, such as the amygdala, are subcortical structures that are illustrated on the cortical surface for ease of presentation. X-System structures are illustrated using a white background color, and C-System structures are illustrated using a black background color. This dual systems perspective is a simplification of real brain mechanisms. Frank et al. [27], among others, provide additional insights into this topic. Prominent neuroeconomists like Camerer et al. [15], along with scholars in other fields, have used the X- and C-Systems Theory to improve understanding of human judgment and decision-making.

has in the past. In this context, Ortiz de Guinea and Markus wrote:

> "Emotions may drive continuing IT use behavior directly (that is, without contributing to the formation of conscious behavioral intentions) [. . .] . [S]udden intense emotions, such as the frustration associated with a system crash or the pleasure aroused while playing a computer game, may be more important in its influence on continuing IT use than intentional behavior driven by relatively stable attitudes and expectations formed during, or as a result of, prior experience with IT use [. . .] . [B]ecause emotion is viewed by many psychologists as a lower level, more basic, driver of human behavior than conscious decision-making, and because emotion-driven behavior may occur largely outside people's awareness, the alternative view suggests that continuing IT use may be much more automatic than the consensus IS view portrays." [53, p. 438]

Because of the direct influence of activity in X-System brain structures (Figure 2) on human behavior [15, 43, 68], the concept of habit comes into focus. In the present context, habit is defined as a phenomenon in which an environmental cue (e.g., the information provided on a user interface or the design of the interface) triggers the activation of a previously learned sequence of actions in a stable context [53, p. 439]. As cognitive neuroscience research [e.g., 33] has already shown, habitual human-computer interaction processes involve significantly less brain activity than does the interaction of humans with computers based on deliberate and conscious thinking. Since this reduced brain activity comes along with significant improvements in performance, IS design science researchers should consider the direct influence of emotions on user behavior and related processes, such as habit, enjoyment, and flow, when building and evaluating artifacts [e.g., 25, 40].

A recent trend in human-computer interaction is the increasing use of social networking functionalities, such as instant messaging and posting of pictures to engage with others. For example, at the end of 2011, the number of daily active Facebook users was 483 million, and the number of monthly active users was 845 million. A recent neurophysiology experiment [48] investigated the affective experience evoked by social networking sites, hypothesizing that strong positive emotions could explain the intensive use of social networking functionalities. Specifically, several neurophysiological parameters that correlate with activity in X-System brain structures (skin conductance, blood volume pulse, EEG, electromyography, respiratory activity, and pupil dilation) were recorded in users during exposure to the subject's personal Facebook account. The results indicate that the Facebook experience was significantly different from that of two control conditions (relaxation and stress). The biological signals showed that Facebook use can evoke a biological state characterized by high positive valence and high arousal, referred to as a core flow state. Therefore, builders and evaluators of IT artifacts should consider the influence of design parameters (e.g., specific functions) on emotions such as flow, as well as the influence of an interface on affective states in general.

In addition to the implications of the X- and C-Systems Theory for the building and evaluation of IT artifacts, the theory has a significant methodological implication for IS design science research. Consider, for example, research on the Technology Acceptance Model (TAM), the most cited theoretical framework in the IS discipline [17, 79], where traditional techniques from the social sciences, such as surveys and interviews, have been used to study a user's beliefs about and attitudes toward the antecedents of technology acceptance.

In its basic form, TAM distinguishes "perceived usefulness" and "perceived ease of use" as antecedents of a user's intention to use a technology. Based on knowledge on this fundamental theoretical mechanism, as well as insights into the specific determinants of usefulness and ease of use [e.g., 1, 54, 78], the model informs both the design and development of an IT artifact by helping to predict certain principles of form and function that may be favored by users in a given context [32]. However, because it is impossible for engineers to anticipate all design factors (e.g., system features and interface design), an empirical evaluation of the IT artifact is considered an important phase in IS design science research [e.g., 58]. Both qualitative and quantitative techniques (e.g., interview and survey) have been used to evaluate the acceptance of artifacts based on a user's perceptions [34].

Despite the significant insights that TAM and related research have provided, one major consequence of asking a user about his or her beliefs and attitudes toward an IT artifact is that the report can comprise only *conscious* perceptions and thoughts. Behavioral intentions and actual behavior are both influenced by deliberate and conscious thinking, but research has provided evidence that both are also strongly influenced by unconscious perceptions and information processing [43]. Recently, IS scholars have debated whether a user's emotions and affective states in particular may significantly affect technology acceptance in general and their behavior toward a specific technology in particular [21, 45, 53, 63].

Automatic processes (X-System) are active most of the time, so they are considered the background mode of brain functioning. In contrast, controlled processes (C-System) become active only when automatic processes are interrupted (e.g., in novel decision situations). Since TAM and its extensions (i.e., TAM++) are primarily built on TRA and TPB, so they focus on controlled, rather than automatic, brain processes, a methodological issue emerges. Therefore, while questionnaire techniques (interview, survey) lead to some insights into the root causes of behavior, their results are limited to information of which informants are aware and which they consciously report, perhaps influenced by social desirability and other biases [18]. Therefore, the reliability of evaluation results based on questionnaire techniques requires attention in IS design science research. Most studies on TAM and TAM++ have asked respondents about their perceptions of how useful and easy to use a system is and what they perceive to be their own level of usage [75]. However, a user usually interacts with a system without consciously thinking about the use process because system use is typically habitual in nature [53]. Therefore, automatic processes dominate system use, and it is difficult for users to provide good introspective accounts about their use because it is so habitual in nature. As a result, the data underlying TAM and TAM++ research may be biased toward conscious processes. In a pioneering article, Ericsson and Simon wrote, "[I]naccurate reports found by . . . research are shown to result from requesting information that was never directly heeded, thus forcing subjects to infer rather than remember their mental processes [23, p. 215]." Therefore, we conclude that consideration of neuroscience theories (here the X- and C-Systems Theory) makes explicit the possibility that biased data underlies traditional research streams (here TAM and TAM++ research). The use of neuroscience tools has been suggested to address this issue [20, 21, 63]. We discuss this idea in detail in the next section.

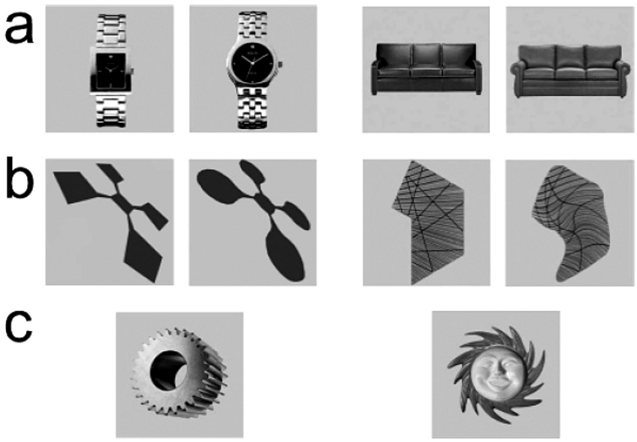

FIGURE 3. Examples of Stimuli Used in the Experiment (Source: [6, p. 646])

Notes: Pairs of real objects (a), pairs of meaningless patterns (b), and control objects (c). Pairs of real objects were matched in appearance and semantic meaning so the contour was the critical difference between them. The control objects, which had a mixture of curves and sharp angles, were used to provide baseline data.

Example 2: Theory on the Human Preference for Curved Visual Objects

In IS design science research, both software systems (which are the focus of many TAM and TAM++ studies) and conceptual models play significant roles. While the origins of conceptual modeling can be traced back to software engineering, several additional purposes of conceptual modeling are apparent in IS, among which are data modeling, knowledge modeling, business process modeling, and enterprise modeling [80].

Research has begun to investigate the acceptance and quality of the model itself and the influence of user perception on the success of the modeling process [e.g., 49, 62, 71, 24]. Because the development of a conceptual model implies the use of a specific modeling notation that consists of graphical elements, composition rules, and a semantic definition of the elements, neuroscience theories on the visual perception of graphical elements (objects) may provide significant insights for conceptual modeling.

Humans always make judgments about objects they encounter in their environment, so when a user is confronted with a conceptual model, he or she makes rapid judgments about the artifact based on its physical properties. Psychological and cognitive neuroscience research has theorized that sharp transitions in shape contour may convey a sense of threat, thereby triggering negative perceptions that may negatively affect the model's comprehensibility and the user's acceptance.

In one experiment [6], participants viewed pictures of real objects, meaningless patterns, and control objects (Figure 3). Each picture was presented for 84ms, and participants were asked to make a like/dislike judgment based on their immediate "gut reactions." Each stimulus was presented in two versions (Figure 3): one with sharp transitions in contour and one with curved transitions. The results of the experiment showed that participants liked the curved objects significantly more than the control objects and that they liked the sharp-angled objects significantly less than the control objects. A similar preference for the meaningless patterns, some of which closely resembled the appearance of conceptual models (e.g., Figure 3b) was found.

Another experiment based on fMRI [7] investigated the neural mechanisms underlying this preference towards curved objects and patterns and found that the amygdala is significantly more active in perceiving everyday sharp objects (e.g., a sofa with sharp corners) than in perceiving their curved contour counterparts (Figure 3a). Because the amygdala is a phylogenetically old brain area that is mainly involved in processing fear and arousal [e.g., 83, 88], these results indicate that a preference for visual objects or patterns that "can be induced by low-level perceptual properties, independent of semantic meaning, via visual elements that on some level could be associated with threat" (p. 2191). Therefore, it seems that the human brain is organized to extract basic contour information immediately in order to derive a warning signal quickly in the presence of potential danger.

Given these results, the success of a specific modeling notation and the comprehensibility and acceptance of a specific model can be predicted. All other factors being equal, modeling notations that are based on sharp-angled objects (e.g., YAWL, Yet Another Workflow Language, http://www.yawlfoundation.org/, see top of Figure 4) and their corresponding artifacts (i.e., specific models developed based on such a language) are less liked (or less comprehended or accepted) than are notations and their corresponding artifacts that are based on curved objects (e.g., BPMN, Business Process Modeling Notation, http://www.bpmn.org/, see bottom of Figure 4). This kind of theorizing illustrates the potential of neuroscience theories in building and

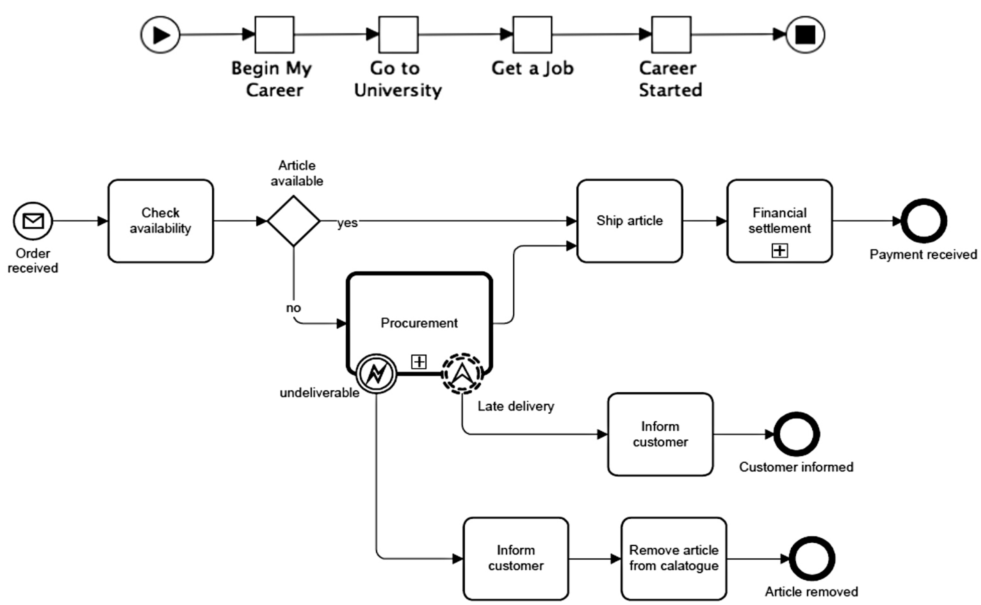

FIGURE 4. Examples of Two Conceptual Models (Sources: *Top*: YAWL – User Manual Version 2.2, p. 51; *Bottom*: BPMN 2.0 by Example Version 1.0, p. 5)

evaluating IT artifacts in IS design science research without using neuroscience tools.

3.2 Application Strategy 2: Use of neuroscience tools to evaluate IT artifacts

Because neuroscience tools can measure brain activity (fMRI, EEG) and other neurophysiological parameters (heart rate, skin response), the effects that IT artifacts may have on users can be captured more objectively by the tools than by traditional instruments (e.g., survey). Therefore, they provide a new type of data set useful in the evaluation of software systems and other IT artifacts. For IS design science research, this new type of data is particularly beneficial because users' emotions triggered by the system may be measured more reliably than with traditional questionnaire techniques. Because emotions are increasingly considered important determinants of technology acceptance (e.g., Davis and Banker in Loos et al. [45], [53]), not using neuroscience tools for the evaluation of IT artifacts could significantly impede progress in IS design science research.

Next, we describe the logic of using neuroscience tools to evaluate IT artifacts. Our illustration is based on an example in which a user interface is evaluated in order to inform its design.

A major IS design research question concerns whether specific parameters (e.g., the information presentation mode, colors, navigation structure, use of avatars) contribute to the accomplishment of specific design goals (e.g., increasing the level of perceived trust in the interface, elevating the level of perceived pleasure during interaction with the interface, reducing the level of perceived stress or uncertainty during the interaction). Because the neuroscience literature offers a number of insights into the neurobiological basis of many IS constructs (e.g., trust, pleasure, stress, uncertainty), this literature can be used as a benchmark for IS design evaluation studies.

For example, a recent review [65] discusses the neural correlates of trust identified based on fMRI. The striatum, in particular, has been identified as crucial brain area that affects trust. Based on this finding, engineers could design several versions of interfaces (e.g., V_1 and V_2) and evaluate the trust-inducing potential of each version. If the presentation of V_1 induces significantly more activity in the striatum than V_2, the conclusion is that users perceive V_1 as more trustworthy than V_2. If design parameters are experimentally manipulated, it may be possible to determine which parameter has influenced the formation of trust in the brain.

Another recent empirical study based on functional brain imaging [19] identified the limbic system — a set of interconnected regions of the brain that are essential to the processing of emotions and affective states — as a core structure in technology acceptance. The limbic system has also been found to play a significant role in trust and distrust perceptions toward IT artifacts, such as websites [22, 64]. Therefore, because trust is an antecedent of technology acceptance [30], brain research suggests that human behavior toward artifacts like user interfaces is strongly influenced by emotions and affective states.

One could argue that the costs associated with such a neurological evaluation are high and that the external validity of the evaluation results may be limited because individuals (in the case of fMRI) are required to lie still on their backs inside a noisy scanner while they are presented screenshots of the user interfaces [63]. Because it is not well understood today whether results from the brain scanner may be generalized to a typical human-computer interaction situation in which a user is sitting comfortably in front the computer, evaluation results based on fMRI studies must be interpreted with caution. Moreover, a one-to-one mapping between mental processes (e.g., trust) and brain areas does not exist, since the brain operates in a many-to-many fashion, so activation in the striatum could be related to another mental process altogether. Despite these limitations, IT artifact evaluation may benefit significantly from fMRI studies.

A well-established finding is that cognitive load is associated with specific EEG patterns. A recent review [2] indicated that electrical activity in the brain generates at least four distinct brain wave patterns (based on continuous EEG). Since two of these patterns, alpha and theta waves, are associated with task difficulty, they may serve as proxies for cognitive load. A user's brain waves may be observed during interactions with different versions of interfaces (e.g., V_1 and V_2) in order to draw conclusions about the cognitive load associated with each version and the design of the interface adjusted to reduce cognitive load.

The variety of neuroscience tools is large, and each tool offers a specific set of strengths and weaknesses. Several NeuroIS publications have provided comprehensive discussions of neuroscience tools [e.g., 18, 63], so this article does not discuss these tools again in detail. However, there is consensus that there is no best tool that dominates the others, so an IS design science researcher who wants to decide whether to use a specific tool for IT artifact evaluation has to make trade-offs. For example, while the spatial resolution of fMRI is high (a few millimeters), its temporal resolution is moderate (a few seconds), and the application costs are high, as equipment costs several million dollars, and facilities cost approximately $500 per hour to rent. In contrast, the spatial resolution of EEG is low (several centimeters), while its temporal resolution is high (milliseconds), and the costs associated with its use are moderate, as equipment can cost in the range of $100,000, and facilities cost approximately $100 an hour to rent.

In addition to the neuroscience tools that measure activity in the brain (e.g., fMRI) and at the surface of the skull (e.g., EEG), a number of neurophysiological tools that may be used for the evaluation of IT artifacts are also available. Examples are skin conductance response (SCR) tools, electrocardiography (ECG), facial electromyography (EMG), and eye-tracking tools. (Cacioppo et al. [14], for example, provided a comprehensive compilation of neurophysiological tools relevant for artifact evaluation.) Such "lightweight" tools are suited not only for application in laboratory environments, as is the case with fMRI, but also for application in natural environments, such as professional work environments. Hence, the external validity of evaluation results is usually higher with "lightweight" tools than with "heavyweight" tools like fMRI.

Endocrinological tools have also been introduced into the IS literature. Riedl et al. [66] report on a laboratory experiment in which they investigated the effects of system breakdown (an error message) on changes in users' levels of cortisol, a major stress hormone, measured via saliva samples. The results of the study show that cortisol levels increased significantly when the system broke down in a human-computer interaction task. Therefore, hormone assessments constitute a promising tool for the evaluation of IT artifacts since they can also be used to evaluate different interface designs based on users' hormonal reactions to them. Riedl and Javor [65] identified a list of hormones that are closely associated with human trust (oxytocin, estrogen, dopamine, serotonin) and distrust (arginine vasopressin, cortisol, testosterone) perceptions, which list may be useful in evaluating user interfaces.

3.3 Application Strategy 3: Use of neuroscience tools as built-in functions of IT artifacts

Neuroscience and neurophysiological data (e.g., EEG, skin conductance, heart rate, pupil dilation) and data based on muscle activity (e.g., facial expressions, speech prosody, gestures) can be used in order to assess the psychological state of a user (e.g., stress or fatigue) based on machine learning algorithms and pattern-recognition techniques [e.g., 31]. Based on this information, a system can automatically adjust its user interface in real time in order to improve a user's performance, productivity, and sense of well-being [56, 60]. The scientific field that deals with such "intelligent systems" is affective computing [e.g., 59], but other fields, particularly brain-computer interaction [84] and neuroergonomics [e.g., 55], have also contributed significantly to the advancement of IT artifacts that use neuroscience tools as built-in functions.

In addition to the academic contributions to the development of such systems, technology firms have recognized the potential of neuroscience in advancing human-computer interaction. For example, every year IBM predicts the future of technology via the IBM "5 in 5 initiative," where the company presents "innovations that will help transform aspects of modern life, making the planet smarter, within the next five years." In December 2011, IBM predicted, "[M]ind reading is no longer a science fiction" [36]. In essence, the firm suggested that affective computing and brain-computer interfaces would become a prevalent reality in the near future, revolutionizing human-computer interaction. Similar ideas and research programs have been presented during the most recent decade by Microsoft and Philips, among others.

The primary objective of one of Microsoft's research projects [39] was to assign statistically distinguishable EEG patterns to certain mental states based on a "low-cost off-the-shelf EEG system" that costs only $1,500. Such mental states and the resulting EEG patterns are necessary inputs for technical systems that need to react "intelligently" with respect to a user's cognition and affect [84]. The classification accuracy in this experiment reached more than 90 percent, prompting Lee and Tan to comment, "[t]his work represents a starting point for a wide range of research work exploring how computers can tune into the activity within our minds to help us perform the tasks of our everyday lives [39, p. 89]." Although Microsoft's idea of brain-computer interfacing was not new at the time [11], commitments of globally acting companies like as Microsoft to systems with built-in neuroscience tools can positively influence future research and development initiatives, particularly because such company investments demonstrate the potential for the practical applicability of neuroscience in the design of information systems.

In essence, Microsoft's research and similar projects in academia seek to replace the input device (e.g., the mouse or keyboard) with a user's conscious thoughts (brain-computer interaction) and unconscious emotional states (affective computing). Studies have provided evidence that basic navigation in virtual worlds (e.g., left, right) can be performed based on a user's thoughts [28, 41, 69]) and that users (including paralyzed people who are unable to speak) may be able to write letters on a computer screen using only their thoughts [11]. Similar research projects are reported in IS outlets [51, 61].

Despite the promising results of recent research and development in brain-computer interaction and affective computing, significant challenges remain. For example, Gökcay and Yildirim write:

> "[T]here are two major obstacles that hinder us from implementing such systems in the near-term: 1. The neuroanatomical underpinnings of the affective processes in the human brain are extremely complex and far from being well understood, hence the field is not quite ready for developing affective models. 2. A dynamical platform to model such a system is hard to implement and validate because affective inputs/outputs should be produced and tested in several different temporal scales, while the affective representations across these temporal scales also overlap [31, p. xvi-xvii]."

Similarly, Riedl and Müller-Putz in Loos et al. [45] argued that theoretical and technical challenges, among other factors, in the field of brain-computer interfaces have impeded the development of commercial products in practice. Therefore, the available systems must still be associated with activities by engineers who implement and run the systems at the user's site.

However, "lightweight" tools that measure the autonomic and somatic nervous system (e.g., electrodermal activity) and the ophthalmic system (eye-tracking) are coming into increasing use. A system prototype developed by Philips and ABN AMRO, a large bank in the Netherlands, provides a useful illustration of a state-of-the-art project in this area.

Private investors often trade securities online, but research shows that financial decisions tend to be suboptimal when an investor is emotionally aroused [42]. For example, investors who are driven by fear may sell too hastily when stock prices fall, and those driven by greed may purchase too many stocks at too high a price [37]. Against this background, Philips and ABN AMRO developed a system prototype and presented it to the public in 2009 under the title "Rationalizer concept: An emotion mirroring system for online traders."

The system measures the emotions of an online investor based on "galvanic skin response (GSR) sensing technology" that measures the level of arousal with an Ohm meter that captures the electrical resistance between two points, typically the wrists or fingers. The more aroused a person is, the more sweat is produced, and sweat increases skin conductance. Users can employ the system's warning of a high level of arousal as a signal to abstain from financial transactions for a time. The major purpose of the system is to reduce the number of unfavorable financial decisions.

The system consists of two components, a bracelet attached to the wrist that measures emotions via skin conductance, and a display device that shows the strength of emotions using light patterns and colors [37]. The display device looks like a bowl, which fits nicely into a domestic environment. Although this prototype is not a "complete" affective computing system because skin conductance is presented to the user via the bowl, rather than being used by the system to adjust the user interface, the simplicity of the components and their use (i.e., measurement takes place at the wrist and not in the brain or at the skull) make clear the system's practical use (Riedl and Müller-Putz in Loos et al. [45]).

4. DISCUSSION

Having described three application strategies for neuroscience in IS design science research, we next outline specific requirements for each of them, discussing issues of applicability, cost, accessibility, knowledge, and prior references.

4.1 Applicability

The application of neuroscience theories and tools is not necessarily of value in all areas of IS research [18]. In IT and individuals, IT and groups, IT and organizations, IT and markets, and IS development, Sidorova et al. [72] distinguished five core research areas in the IS discipline. While most IS publications that make use of neuroscience theories and tools may be located in the first of these areas, this paper explores the last one, which "examines the information technology itself, and how it is developed" [72, p. 475]. This approach is in line with the conceptualization of NeuroIS by Riedl et al. [63, p. 245], who proposed the use of neuroscience theories and tools in the design of IT artifacts.

Emotions have been recognized as an essential factor in technology acceptance (e.g., Davis and Banker in Loos et al. [45]). While neuroscience theories can help to predict the emotional effects of design decisions (Strategy 1), evaluations can help to assess the affective outcomes of an artifact design in a given context (Strategy 2). IT artifacts with built-in neuroscience tools may even adjust to the affective state of the user (Strategy 3), thereby blurring the boundary between humans and machines.

While neuroscience thus offers a new lens through which the design of IT artifacts can be studied (in this case, the affective one), additional aspects of design should be considered as well. In particular, for each of the strategies proposed, neuroscience theories and tools should be used to complement the traditional techniques of data collection and analysis, rather than to replace them [63, 80]. However, even such complementary use may not be beneficial in all situations; IS researchers who engage in this particular field of research should reflect on whether and to what extent the application of neuroscience can support the design of IT artifacts in their individual situations.

4.2 Cost

From a pragmatic perspective, the cost of applying one of the three strategies must be balanced with the benefits that can be expected. In particular, the use of neuroscience tools in design-oriented research (Strategies 2 and 3) entails considerably higher costs than those associated with conventional tools like surveys and interviews, both in terms of initial investment and operational costs. However, cost differs significantly among the various tools. Dimoka et al. [18] wrote, "[W]hile the cost of psychophysiological tools is manageable, the cost of neuroimaging tools is substantial (about USD$100-600 per scanning hour), given the need for technicians with specialized knowledge". Likewise, Loos et al. [45], Riedl et al. [63], and vom Brocke et al. [80] distinguish between the costs of heavyweight and lightweight tools for use in NeuroIS.

While it is not possible to derive general conclusions about the costs associated with the three application strategies presented, they tend to increase from Strategy 1 to Strategy 3. That is, the use of neuroscience theories in a design-oriented research endeavor (Strategy 1) comes at significantly lower cost (if any at all) than the application of neuroscience tools in IT artifact evaluation (Strategy 2), which costs less than the use of neuroscience tools as built-in functions of IT artifacts (Strategy 3).

However, the three strategies are not to be seen as independent one from the other but as building on one another. An artifact evaluation using neuroscience tools (Strategy 2) usually requires an understanding of neuroscience theories (Strategy 1) in order to interpret the data. Implementing neuroscience built-in functions in IT artifacts (Strategy 3) frequently means utilizing tools for real-time evaluation (Strategy 2), which draws upon neuroscience theories (Strategy 1). Hence, IS researchers are advised to assess the costs at the outset of any design science study that intends to draw from neuroscience tools and theories.

4.3 Accessibility

IS researchers have to consider aspects of accessibility [18, 63] when they plan to use neuroscience in a design science project. Neuroscience tools are not usually available "in-house" in IS departments but must be accessed in medical facilities or universities that focus on neuroscience, biology, and/or psychology (Strategies 2 and 3). The acquisition and use of neuroscience tools is relatively expensive, and the capabilities required to use the tools are substantial.

While neuroscience theories basically are available in most libraries and academic databases, still accessibility might also be an issue for Strategy 1 because the knowledge needed to identify, understand, and appropriately use neuroscience theories is substantial. This poses an important challenge to IS research as a vast literature on neuroscience exists, increasing the risk of misinterpreting and incorrectly utilizing the theories and tools from this field. Hence, the application of the strategies presented may require the establishment and cultivation of inter-disciplinary collaborations. Importantly, most NeuroIS papers published in leading IS journal have involved such interdisciplinary collaborations with academics from cognitive neuroscience and neuroeconomics [20, 64], indicating the usefulness of this strategy.

4.4 Knowledge

Neuroscience has only recently found its way into IS research. While the level of publication activity in the field is generally increasing, only a few IS publications use neuroscience tools and/or theories, and there are even fewer guidelines on how to plan and conduct NeuroIS design science studies. As NeuroIS is an emerging field of research in the IS discipline, many researchers in the field may not yet have the necessary knowledge to implement the proposed application strategies in their research program.

Generally, the degree of knowledge required implementing the strategies increases from Strategy 1 to Strategy 3; for example, designing an IT artifact with a built-in neuroscience functionality (Strategy 3) requires more knowledge than to use neuroscience tools evaluating IT artifact (Strategy 2), which requires more knowledge than does using a neuroscience theory to inform the design of an IT artifact (Strategy 1). For example, the results of the experiment by Bar and Neta [6], which suggest that model users prefer curved model elements over sharp-angled ones (Strategy 1), are directly relevant to designers of conceptual models. However, if you intend to measure model adoption at the level of the individual user with the help of neuroscience tools (Strategy

2) or to enable real-time variations of a model representation considering the affective state of the user (Strategy 3), significantly more neuroscience knowledge would be required.

4.5 References

Only few examples in IS design science research draw from the field of neuroscience, so IS researchers who plan to apply one of the three strategies presented are likely to find it difficult to identify earlier works to serve as references for planning their research and organizing their papers. However, as the illustrative examples show, IS researchers can refer to several related disciplines. For instance, the use of neuroscience tools as built-in functions of IT artifacts (Strategy 3) can draw from more established fields, such as affective computing [59] and neuroergonomics [54], and in the evaluation of IT artifacts using neuroscience measurement tools (Strategy 2), IS scholars can refer to related works in the fields of usability research [35] and HCI [26]. In these fields, studies applying psychophysiological tools (e.g., eye tracking, galvanic skin response) in order to evaluate user interfaces already have a long tradition, and also brain-imaging tools have been used in such studies frequently.

In the IS discipline, we already see research papers that investigate the effect of IT artifacts on users (e.g., trust in Riedl et al. [64]). Even though such studies have typically tested or built theory rather than designing IT artifacts, they have also informed the evaluation of systems by means of neuroscience tools (Strategy 2). Finally, the remarkable body of knowledge that originates from neuroscience can be used to inform the design and evaluation of IT artifacts (Strategy 1). Insights on the perception of shapes of objects are examples. Subfields like neuroeconomics [e.g., 15] and neuromarketing [e.g., 4] also offer valuable insights. Hence, while only a few references are available in the IS discipline, IS scholars are advised to explore neighboring disciplines.

4.6 Summary

In table 1 we give a summary of the requirements discussed for each application strategy of neuroscience in IS design science research as identified in the taxonomy.

TABLE 1. Requirements of the Three Application Strategies

	Use of neuroscience theories to inform the building and evaluation of IT artifacts	*Use of neuroscience tools to evaluate IT artifacts*	*Use of neuroscience tools as built-in functions of IT artifacts*
Applicability	Informing the design and evaluation of IT artifacts in terms of the potential emotions and affective responses that result from diverse design decisions.	Providing means by which to collect data on the affective effects stimulated by the IT artifact on certain users in a given context.	Providing means by which to build systems that use real-time neurophysiological data from users to adapt the systems functionality and/or interface automatically.
Cost	Cost of taking up the academic literature in the field of neuroscience.	Cost of using neurophysiological measurement tools and cost of planning and interpreting the evaluation (differs significantly based on the specific types of measurement tools). See Riedl et al. [63] for a thorough review of tool costs.	Cost of integrating a neuro-sensitive device in the IT artifact and linking it to the artifact's functionality and/or interface.
Accessibility	Available in most libraries and academic databases.	Access to neuroscience tools (e.g., in medical units, HCI centers, and NeuroIS labs).	Access to laboratories to build neuro-sensitive devices (e.g., technical engineering labs).
Knowledge	Knowledge of the specific neuroscience theories of interest. Discussing the theories with experts from outside the IS community is recommended.	Knowledge of how to conduct neuroscience data collection, analyses, and interpretation using the measurement tool of choice. Involving experts from outside the IS community is recommended.	Knowledge on both the specific neuroscientific measurement capability of the device and the engineering of the IT artifact. Involving experts from outside the IS community is recommended.
References	Studies in the field of neuroscience in general and neuroecomomics in particular can serve as examples.	Usability studies and HCI research offer examples of evaluating IT artifacts by means of different kinds of neuroscience tools.	Engineering initiatives in disciplines like affective computing and neuroergonomics can serve as references from neighboring fields of research.

5. CONCLUSION

The aim of this paper was to present a taxonomy of application strategies for neuroscience in IS design science research. We identified three general application strategies — the use of neuroscience theories to inform the building and evaluation of IT artifacts, the use of neuroscience tools to evaluate artifacts, and the use of neuroscience tools as built-in functions of artifacts — and discussed them based on several illustrative examples. This article constitutes a first step toward systemizing the role of neuroscience theories and tools in IS design science, complementing related works that present a broader neuroscience agenda for IS research [18]. In particular, we extend earlier works that have accentuated the potential of neuroscience in IS design science research [e.g., 12, 20, 42, 63, 67, 80]. With the three application strategies, we hope to support fellow researchers in applying neuroscience theories and tools in their design studies and to contribute to establishing NeuroIS as a promising field for design science studies.

We also discussed specific requirements associated with the use of neuroscience tools and theories in design science, addressing issues of applicability, cost, accessibility, knowledge, and available references. While all of these strategies stress considering the emotions and affective states of the user in design science research, we characterized the three strategies as being complementary and hierarchical. Thus, IS researchers should begin with Strategy 1, whose overall level of complexity (as measured by the five requirements) is lowest. Strategy 2 can follow, while Strategy 3, which has the highest level of complexity in terms of its required knowledge of neuroscience theories and tools, as well as technical engineering knowledge (e.g., an artifact's functionality being responsive to real-time bio-signals of the user), should be last.

We acknowledge that the taxonomy presented is only a first step toward systemizing the role that neuroscience could play in design science. Future research should clarify this role and lead to more specific guidelines for NeuroIS from the perspective of design science — including, in particular, investigation into typical design decisions with respect to the emotional effect of IT artifacts — because there may be important differences in the perception of conceptual models and software systems, just to name a few. Guidelines for collecting and interpreting neuroscience data regarding the evaluation of IT artifacts are needed, including the selection of appropriate neuroscience tools for specific types of artifacts. Furthermore, with the growing affordability and use of neuroscience tools for corporate use [e.g., 86], future steps also shall involve translating these strategies in actionable guidelines and best practices to foster the adoption by IS practitioners. Finally, it will be rewarding to explore systematically areas of practical application for IT artifacts with built-in "neuro-functionality" — the first significant contributions have already been made by firms like Microsoft and Philips — because it is important for an applied science like IS to contribute to the development of IT artifacts in order to "lend utility to theory" [9, p. 271].

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