Information Systems Research

Publication details, including instructions for authors and subscription information:
http://pubsonline.informs.org

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Information Systems Research
Vol. 22, No. 4, December 2011, pp. 687–702
ISSN 1047-7047 | EISSN 1526-5536 | 11 | 2204 | 0687
http://dx.doi.org/10.1287/isre.1100.0284

Research Commentary

NeuroIS: The Potential of Cognitive Neuroscience for Information Systems Research

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This paper introduces the idea of drawing upon the cognitive neuroscience literature to inform IS research (herein termed "NeuroIS"). Recent advances in cognitive neuroscience are uncovering the neural bases of cognitive, emotional, and social processes, and they offer new insights into the complex interplay between IT and information processing, decision making, and behavior among people, organizations, and markets.

The paper reviews the emerging cognitive neuroscience literature to propose a set of seven opportunities that IS researchers can use to inform IS phenomena, namely (1) localizing the neural correlates of IS constructs, (2) capturing hidden mental processes, (3) complementing existing sources of IS data with brain data, (4) identifying antecedents of IS constructs, (5) testing consequences of IS constructs, (6) inferring the temporal ordering among IS constructs, and (7) challenging assumptions and enhancing IS theories.

The paper proposes a framework for exploring the potential of cognitive neuroscience for IS research and offers examples of potentially fertile intersections of cognitive neuroscience and IS research in the domains of design science and human-computer interaction. This is followed by an example NeuroIS study in the context of e-commerce adoption using fMRI, which spawns interesting new insights. The challenges of using functional neuroimaging tools are also discussed. The paper concludes that there is considerable potential for using cognitive neuroscience theories and functional brain imaging tools in IS research to enhance IS theories.

Key words: cognitive neuroscience; functional brain imaging; NeuroIS; neuroeconomics; neuromarketing
History: Ritu Agarwal, Senior Editor and Associate Editor. This paper was received on July 10, 2008, and was with the authors 6 months for 2 revisions. Published online in *Articles in Advance* April 14, 2010.

1. Introduction

To understand the complex and elusive issues concerning the interplay of IT with information processing, decision making, and behavior in individuals, groups, organizations, and markets, IS research has long drawn upon leading reference literatures. Over the past decade, cognitive neuroscience has generated many advances in the basic understanding of information processing, decision making, and behavior by directly and objectively measuring the brain activity that underlies various decision-making, cognitive, emotional, and social processes. Economists, psychologists, marketers, and other social scientists are teaming up with cognitive neuroscientists, and many novel insights are emerging as a result of directly asking the brain, not the person, and opening the brain's "black box" (e.g., Camerer et al. 2004, Glimcher and Rustichini 2004, Lee et al. 2007, Phan et al. 2002). We propose that the cognitive neuroscience literature can also offer new cutting-edge foundations and serve as a reference discipline for IS research that could help further advance our knowledge of the complex interplay of IT and information processing, decision making, and behavior. The purpose of this commentary is to introduce cognitive neuroscience theories, methods, and tools to IS researchers and encourage them to consider taking advantage of their potential by answering two questions: How can the cognitive neuroscience literature inform IS research? How can IS researchers use brain imaging tools to complement their existing sources of data?

Given the potential of cognitive neuroscience to revolutionize the social sciences (*Economist* 2005), we argue that IS researchers can also benefit from by drawing upon the theories, methods, and tools offered by cognitive neuroscience. There is a rich literature on how people process information (e.g., Ferstl et al. 2005), make economic and social decisions (Hsu et al. 2005), deal with uncertainty and ambiguity (Krain et al. 2006), respond to rewards (McClure et al. 2004a), make purchases (Deppe et al. 2005), predict the behavior of others (McCabe et al. 2001), trust and cooperate (King-Casas et al. 2005), make calculations (McClure et al. 2004b), and act upon emotional and cognitive stimuli (Ioannides et al. 2000). Since a deeper understanding of the underlying brain activity involved in mental processes can enhance our understanding of how IT can facilitate information processing, decision making, and behavior, many of the rapid advances in cognitive neuroscience could help inform IS research by establishing a novel and relatively distinct foundation of literature, theories, methods, and tools that has the potential to accelerate the progress of IS research. Currently, IS researchers are beginning to explore the potential of cognitive neuroscience for IS research (e.g., Dimoka et al. 2007, Dimoka 2010, Moore et al. 2005, Randolph et al. 2006). Nonetheless, we propose that IS research could benefit by leveraging the rapidly evolving cognitive neuroscience literature in the social sciences to enrich IS theories concerning the interplay of IT with human information processing, decision making, and behavior.

IS researchers typically collect data from surveys, field and lab experiments, interviews, secondary sources, and simulated models. While these data sources have certainly advanced IS research—by directly asking the brain, not the person—brain imaging tools might offer objective and unbiased measurement of decision-making, cognitive, emotional, and social processes. Since functional brain imaging tools are becoming more accurate, accessible, and affordable, IS research can complement existing data sources with brain data, particularly for measuring mental processes that people might be unable or unwilling to self-report. Given that self-reported data could be susceptible to multiple measurement biases (e.g., subjectivity, social desirability, common methods), complementing existing sources of IS data with functional brain imaging data would help triangulate different measurement methods and data sources, and thereby strengthen the robustness of empirical IS studies.

Therefore, the cognitive neuroscience literature and functional brain imaging tools applied to IS research (termed "NeuroIS") are proposed to spawn seven opportunities for IS research (Table 1): (1) localize the brain areas associated with IS constructs, (2) capture hidden processes, (3) complement existing sources of data, (4) identify antecedents of IS constructs, (5) test consequences, (6) infer causality, and (7) challenge IS assumptions.

The paper proceeds as follows. Section 2 offers examples of how neuroeconomics and neuromarketing have informed economics and marketing theories, provides an overview of brain anatomy and functionality, identifies several mental processes that relate to IS research, and offers a review of their associated brain areas. Section 3 elaborates on the proposed seven opportunities of cognitive neuroscience for IS research (Table 1) and offers examples in the context of e-commerce, design science, and human-computer interaction. Section 4 outlines the general structure and steps of a NeuroIS study and offers an example NeuroIS study that examines the technology acceptance constructs in the context of e-commerce. Section 5 discusses the opportunities and implications of taking advantage of cognitive neuroscience literature and brain imaging tools in IS research.

Table 1 The Proposed Opportunities for IS Research

(1)	Localize the various brain areas associated with IS constructs (neural correlates of IS constructs) and link them to the cognitive neuroscience literature to map IS constructs into specific brain areas, learn about the functionality of these brain areas, and better understand the nature and dimensionality of IS constructs.
(2)	Capture hidden (automatic or unconscious) mental processes (e.g., habits, ethics, deep emotions) that are difficult or even impossible to measure with existing measurement methods and tools.
(3)	Complement existing sources of data with brain imaging data that can provide objective responses that are not subject to measurement biases (e.g., subjectivity bias, social desirability bias, common method bias).
(4)	Identify antecedents of IS constructs by examining how brain areas are activated in response to IT stimuli (e.g., designs, systems, websites) that intend to enhance certain outcomes (use behavior, productivity).
(5)	Test consequences of IS constructs by showing whether, how, and why brain activation that is associated with certain IS constructs can predict certain behaviors (e.g., system use, online purchasing).
(6)	Infer causal relationships among IS constructs by examining the temporal order of brain activations (timing of brain activity) stimulated by a common IT stimulus that activates two or more IS constructs.
(7)	Challenge IS assumptions by identifying differences between existing IS relationships and the brain's underlying functionality, thus helping to build IS theories that correspond to the brain's functionality.

2. Literature Review

2.1. Example Studies from Neuroeconomics, Neuromarketing, and NeuroIS

The ability to link brain activity to human behavior has highlighted the potential of cognitive neuroscience for the social sciences. Economics and psychology pioneered this trend, followed by marketing, and many interesting findings are emerging in these respective disciplines from functional brain imaging studies. Also, Glimcher and Rustichini (2004) argue that neuroeconomics, psychology, and neuromarketing are converging to provide a unified theory of human behavior by integrating economics, psychology, and marketing under the umbrella of cognitive neuroscience in the social sciences. Table 2 briefly reviews some representative examples of research findings in neuroeconomics and neuromarketing, and it also cites some emerging work in NeuroIS.

2.2. Overview of Brain Anatomy and Functionality

Using functional brain imaging tools, the cognitive neuroscience literature focuses on the localization and

Table 2 Example Studies from Neuroeconomics, Neuromarketing, and NeuroIS

What is neuroeconomics?

Neuroeconomics is the application of cognitive neuroscience to economic behavior using functional brain imaging tools. Neuroeconomics develops models of economic behavior that are based on measurement of brain activations that underlie human processes, behavior, and decision making in experimental games where subjects are given different tasks and payoffs (e.g., Rustichini 2005). For a detailed review of the neuroeconomics literature, please see Camerer et al. (2004).

Example neuroeconomics studies

Cognitive and emotional aspects of decision making: Bhatt and Camerer (2005) showed that decision-making processes have both cognitive and emotional aspects, and subjects whose brain activity displayed good cooperation between the limbic system (emotional area) and the prefrontal cortex (cognitive area) were the best performers in experimental games.

Decision making under uncertainty and ambiguity: Hsu and Camerer (2004) showed that a brain area (insular cortex) that is activated in response to adverse bodily states, such as pain, is activated when subjects have to choose among ambiguous gambles. Yet this area is not activated when the subjects choose between certain or even uncertain gambles. These results help explain why people loathe ambiguous situations and prefer gambles with unambiguous probabilities.

Anticipation of gains and losses: The neuroeconomics literature showed that different neural mechanisms govern the anticipation of gains and losses. Functional brain imaging studies showed that the human brain processes information about gains and losses in different areas. For example, Kuhnen and Knutson (2005) showed that the prospect of a $5 gain activated a different brain area compared to the prospect of a $5 loss. These findings are consistent with prospect theory (Kahneman and Tversky 1979), which proposes that people weigh gains and losses differently.

Evaluating payoffs and outcomes: Smith et al. (2002) show attitudes about payoffs and beliefs on expected outcomes to interact behaviorally and neurally, challenging an economic assumption that payoffs and outcomes are independent.

What is neuromarketing?

Neuromarketing is the application of cognitive neuroscience theories and functional brain imaging tools to marketing. By understanding how the human brain activates in response to marketing and advertising stimuli (Zaltman 2003), neuromarketing aims to build superior models to understand consumer behavior and market products (Lee et al. 2007). For a comprehensive review of the neuromarketing literature, please see Lee et al. (2007).

Example neuromarketing studies

Consumer behavior: Deppe et al. (2005) showed that a person's first brand choice activates an area associated with social decision making, while the second brand choice activates an area associated with cognitive processes. These findings imply impulse versus planned behavior. McClure et al. (2004b) showed that *immediate* versus *delayed* rewards activate distinct brain areas, implying a battle of intertemporal trade-offs between impulse and planned purchases.

Consumer preferences: McClure et al. (2004c) tried to explain the consumers' preference for Coke over Pepsi. Using functional brain imaging (fMRI) tools, the authors show activation of the dorsolateral prefrontal cortex (a brain area implicated in cognitive information processing) when notifying subjects that they are drinking Coke. However, no such activation was observed when subjects were notified that they are drinking Pepsi. The authors explained these results by implying that the Coke's preference was due to cognitive information biasing preference choice.

Purchase choice: Braeutigam et al. (2004) used magneto-encephalogram brain imaging technique (MEG) to identify differences in brain activation between predictable and unpredictable choices. The authors showed that different brain regions are activated in response to choice predictability, with unpredictable choices eliciting brain activations in regions associated with silent vocalization and judgment of immediate versus delayed rewards.

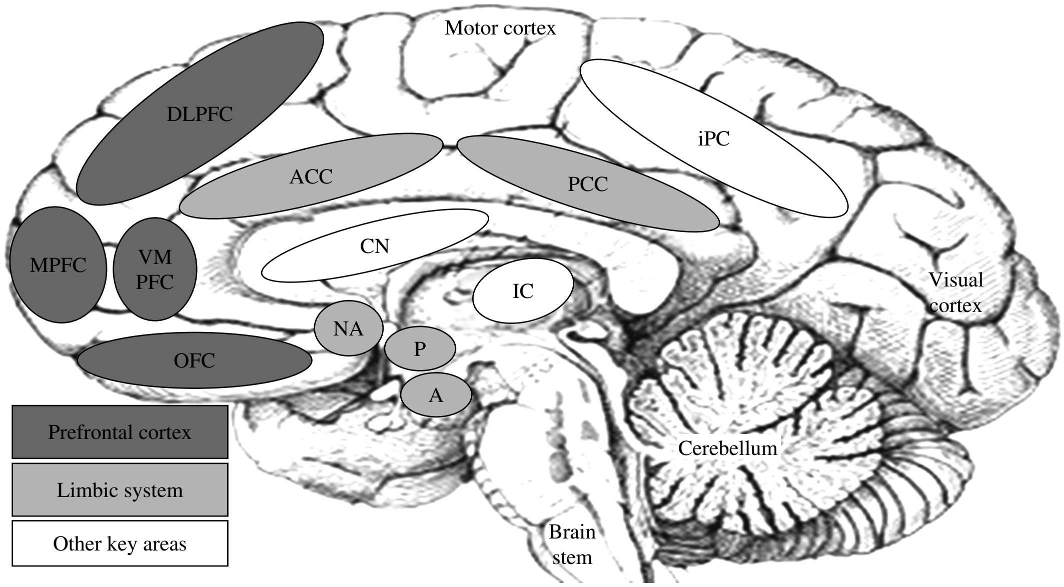
Brand advertising: Ioannides et al. (2000) identified the brain areas related to brand advertising stimuli. Young (2002) showed with brain data the role of advertising in brand development, awareness, and attention, while Rossiter et al. (2001) showed that visual images that created fast brain activation in the prefrontal cortex spawned strong brand recognition.

Emerging NeuroIS studies

In IS research, there have been some recent attempts to use cognitive neuroscience theories and tools. Moore et al. (2005) and Randolph et al. (2006) used EEG to study brain-computer interaction for handicapped patients. Dimoka and Davis (2008) identified where the TAM constructs reside in the brain. Dimoka et al. (2009) found differences in brain activity among women and men when they interacted with recommendation agents whose avatars varied in their race and gender. Adomavicius et al. (2009) contrasted various combinatorial auctions interfaces by examining the activation in the brain's "cognitive overload" areas. Finally, Dimoka (2010) showed that trust and distrust span distinct brain areas using fMRI.

In the IT industry, Microsoft uses EEG for task classification and activity recognition (http://blogs.zdnet.com/BTL/?p=6609). Similarly, Emotiv (http://www.emotiv.com) uses EEG-based headsets to observe brain activity of video game users.

Figure 1 The Major Areas of the Brain



Note. DLPFC: dorsolateral prefrontal cortex; VMPFC: ventromedial prefrontal cortex; OFC: orbitofrontal cortex; MPFC: medial prefrontal cortex; ACC/PCC: anterior/posterior cingulate cortex; NA: nucleus accumbens; A: amygdala; CN: caudate nucleus; P: putamen; IC: insular cortex; iPC: inferior parietal cortex.

functionality of the brain areas that underlie decision-making, cognitive, emotional, and social processes. Figure 1 shows some key brain areas that are activated in response to mental processes.[1] The prefrontal cortex is the anterior (front) part of the brain and is often associated with cognitive and social processes, such as problem solving, thinking, calculation, and goals. The key areas of the prefrontal cortex are the dorsolateral (upper outer), ventromedial (lower middle), medial (middle), and orbitofrontal (above the eyes) cortices.

The limbic system consists of the interior parts of the brain that are often associated with emotional processes and feelings (Lautin 2001). Key limbic areas include the cingulate cortex, caudate nucleus, nucleus accumbens, and amygdala. Despite the classic distinction between the prefrontal cortex being associated with cognition and the limbic system with emotions, the mechanisms of emotion and cognition are intertwined (Pessoa 2008), and emotional and cognitive processes often interact extensively (Phelps 2006). For instance, the prefrontal areas support the cognitive regulation of emotions (Ochsner et al. 2002). Thus, the division between the "thinking" and "emotional" brain might be too simplistic, and understanding cognition does require the study of emotions.

2.3. Review of Cognitive Neuroscience Literature Related to Constructs of Interest to IS Research

The past decade has witnessed major advances in decision making, information processing, and behavior resulting from the cross-disciplinary collaborations between brain scientists, psychologists, and economists. The literature has focused on localizing the neural correlates of mental processes, and our review (Online Appendix 1)[2] focuses on constructs that might be relevant to IS researchers. As summarized in Table 3, these mental processes are herein grouped in four categories (decision making, cognitive, emotional, and social) to reflect the variety of processes examined in the cognitive neuroscience literature. This review is not exhaustive, and our proposed categorization simply aims to capture the breadth of mental processes that may be of interest to IS researchers.

3. Proposed Opportunities for Information Systems Research

This section proposes and discusses how IS researchers can take advantage of the emerging literature on cognitive neuroscience and how to use functional brain imaging tools to better understand IS phenomena.

[1] Brain activation is associated with increased blood flow in a brain area in response to any human activity, such as visual, motor, sensory, or mental processes. Brain activation is measured by functional brain imaging tools such as fMRI that capture changes in blood supply (hemodynamic response) to brain neurons that need oxygen to function.

[2] An electronic companion to this paper is available as part of the online version that can be found at http://isr.journal.informs.org/.

Table 3 Review of Cognitive Neuroscience Literature Related to Constructs of Interest to IS Research

Process/construct	Sample brain areas	Key references (cited in Online Appendix 1)
	Decision-making processes	
Calculation	Prefrontal cortex, anterior cingulate cortex	Ernst and Paulus 2005, McClure et al. 2004b
Uncertainty	Orbitofrontal and parietal cortex	Krain et al. 2006, Huettel et al. 2005
Risk	Nucleus accumbens	Knutson et al. 2001
Ambiguity	Parietal cortex and insular cortex	Krain et al. 2006
Loss	Insular cortex	Paulus and Frank 2003
Rewards and utility	Nucleus accumbens, caudate nucleus, putamen	McClure et al. 2004a, Delgado et al. 2005
Intentions	Ventrolateral prefrontal cortex	Dove et al. 2008, Okuda et al. 1998
Task intentions	Medial and lateral prefrontal, anterior cingulate cortex	Haynes et al. 2007, Winterer et al. 2002
Motor intentions	Premotor and parietal cortex	Desmurget et al. 2009, Lau et al. 2007
	Cognitive processes	
Info processing	Medial orbitofrontal cortex, anterior frontal cortex	Elliot et al. 1997, Ferstl et al. 2005
Cognitive effort	Dorsolateral prefrontal cortex, parietal cortex	Owen et al. 2005, Linden et al. 2003
Working memory	Dorsolateral prefrontal cortex	Braver et al. 1997, Cohen et al. 1997
Multitasking	Frontopolar cortex	Dreher et al. 2008
Automaticity	Frontal and striatal cortex, parietal lobe (deactivation)	Kubler et al. 2006, Poldrack et al. 2005
Habit	Basal ganglia, medial prefrontal cortex	Graybiel 2008, Salat et al. 2006.
Priming	Posterior superior cortex, middle temporal cortex	Wible et al. 2006
Spatial cognition	Hippocampus, medial temporal lobe	Moser et al. 2008, Shrager et al. 2008.
Flow	Dorsal prefrontal cortex, medial parietal cortex	Katayose 2006, Iacobini et al. 2004
	Emotional processes	
Pleasure/enjoyment	Nucleus accumbens, anterior cingulate cortex, putamen	Sabatinelli et al. 2008, McLean et al. 2009
Displeasure	Superior temporal gyrus, amygdala, insular cortex	Britton et al. 2006, Casacchia 2009
Happiness	Basal ganglia (ventral striatum and putamen)	Murphy et al. 2003, Phan et al. 2002
Sadness	Subcallosal cingulate cortex	Murphy et al. 2003, Phan et al. 2002
Anxiety	Ventromedial prefrontal cortex, amygdala	Bishop 2007, Wager 2006
Disgust	Insular cortex	Lane et al. 1997, Phan et al. 2002
Fear	Amygdala	LeDoux 2003, Phan et al. 2002
Anger	Lateral orbitofrontal cortex	Murphy et al. 2003
Emotional processing	Medial prefrontal cortex, anterior cingulate cortex	Damasio 1996, Phan et al. 2002
	Social processes	
Social cognition	Temporal lobe, right somatosensory cortex	Adolphs 1999, 2001
Trust	Caudate nucleus, putamen, anterior paracingulate cortex	King-Casas et al. 2005, Dimoka 2010
Distrust	Amygdala, insular cortex	Winston et al. 2002, Dimoka 2010
Cooperation	Orbitofrontal cortex	Rilling et al. 2002
Competition	Inferior parietal cortex, medial prefrontal cortex	Decety et al. 2004
Theory of mind	Medial prefrontal cortex, anterior paracingulate cortex	McCabe et al. 2001
Moral judgments	Frontopolar cortex, posterior superior temporal sulcus	Borg et al. 2006, Moll et al. 2005

Opportunity 1: Localizing Neural Correlates of IS Constructs

A fundamental task for cognitive neuroscience is to localize mental processes onto the brain by linking a mental process into one or more brain areas. Neuroimaging data capture brain activity when a subject performs a mental or behavioral task, thereby essentially mapping mental processes to specific brain areas (Figure 1). Because the cognitive neuroscience literature has already identified the neural correlates of many mental processes and created maps of the brain (Table 3), IS researchers can learn about the functionality of the brain areas associated with IS constructs by localizing their neural correlates and drawing upon knowledge of their functional roles. In other words, IS researchers can shed light on the nature of IS constructs by mapping them into brain areas with existing functional or neurological connotations from the cognitive neuroscience literature.

While a simple interpretation is a "one-to-one" mapping between a brain area and a mental process, there is a more complex "many-to-many" relationship between brain areas and mental processes. In general, a certain process might activate more than one brain area, while a brain area might be activated by more than one process (Price and Friston 2005). Thus, activation in a brain area does not necessarily entail that a mental process is involved (a phenomenon called *reverse inference*). Some studies, alas, tried to incorrectly imply the existence of a mental process when a certain brain area was activated (Miller 2008). This is because reverse inference is "not deductively valid" (Poldrack 2006, p. 59), even if it can still provide some information, such as proposing hypotheses in an exploratory sense and disconfirming theory-driven hypotheses (e.g., Caccioppo et al. 2008). Since there is no one-to-one mapping between mental processes and brain areas, each IS construct could map into several brain areas that jointly underlie the construct. Such mapping can shed light on the nature of the IS construct and whether its neural correlates have specific connotations depending on their exact localization, thus helping guide their conceptualization. For example, the prefrontal cortex is often associated with more cognitive processes, while the limbic system is typically associated with more emotional processes (Figure 1). Such localization can also shed light on the dimensionality of IS constructs by inferring which brain areas are associated with an IS construct. If an IS construct spans several brain areas with distinct functional attributions, this might imply a set of distinct dimensions, suggesting a multidimensional nature. In contrast, if two allegedly distinct IS constructs activate the exact same brain areas, this might imply a commonality that has not been formally theorized in the IS literature. Summarizing Opportunity 1, the localization of the neural correlates of IS constructs with neuroimaging data can shed light on their nature, conceptualization, and dimensionality.

Opportunity 2: Capturing Hidden Processes with Brain Imaging Data

Functional brain imaging tools can capture hidden (unconscious or automatic) processes that cannot be easily or reliably measured with self-reported data because subjects might not be able or willing to express them verbally or behaviorally. Self-reports to sensitive issues (e.g., ethics) might be subject to social desirability bias, while responses to automatic or unconscious processes (e.g., habits) might be difficult or impossible to measure. Neuroimaging studies can be designed to trigger unconscious processes, such as hidden or automatic processes, that are not open to introspection and self-reporting. For example, Haynes et al. (2007) identified the neural correlates of hidden intentions in the brain by triggering different behavioral intentions. Rees et al. (2002) showed that there are distinct neural correlates for conscious and unconscious visual stimuli. Studies can use masked stimuli that are not consciously observed but might still trigger brain activity. Naccache and Dehaene (2001) used briefly presented words that subjects were not consciously aware of (masked semantic priming), which spawned measurable brain activity. Lau and Passingham (2007) showed activity in the mid-dorsolateral prefrontal cortex in response to unconscious priming, challenging the literature that assumed that conscious priming only activates the prefrontal cortex. Neuroimaging studies might thus open many opportunities for IS researchers to examine unconscious, hidden, and automatic constructs that could not be easily measured before.

Opportunity 3: Complementing Existing Data Sources with Brain Data

Brain imaging data can complement existing sources of IS data, especially when extant sources of data are difficult to obtain, biased, questionable, or potentially unreliable. For example, self-reported data might suffer from subjectivity bias, social desirability bias, common method bias, and demand effects. Mast and Zaltman (2005) thus posed the question: "But if questionnaires, verbal reports and interviews all fail to predict behavior, what other methods are there we could use instead?" While brain data might be more costly and difficult to get compared to verbal self-reports, they have some attractive properties because they are direct and objective and do not suffer from the same biases as self-reported data. For example, research on emotions has suffered due to the subjectivity involved in reliably measuring emotions with self-reports (LeDoux 2003). In fact, Dimoka (2010) showed that the emotional (but not the cognitive) brain areas associated with trust and distrust to be weakly correlated with their corresponding self-reported measures of trust and distrust. Knutson et al. (2007) showed the brain measures of preference and value to predict purchasing activity above and beyond self-reported measures. Thus, cognitive neuroscience can help integrate research on emotional and cognitive processes (LeDoux 2003). While we do not question existing sources of IS data, brain data could be a complementary source of IS data, thereby offering IS researchers another useful tool in their repository to triangulate across various data sources. According to Yoon et al. (2009, p. 19), "Researchers should seek convergent validity by linking fMRI data to other behavioral measures." Accordingly, we believe that such convergence would enhance IS research.

Opportunity 4: Identifying Antecedents of IS Constructs

Brain imaging tools can test whether and how IT stimuli—such as IT designs, systems, and prototypes—spawn brain activation in areas mapped by IS constructs. For example, whether an IT artifact increases a system's usefulness can be objectively tested by showing activation in the brain's utility areas. For example, IS research has shown a weak link between intentions to use a system and actual usage (Straub et al. 1995). Besides, information overload and cognitive effort (which can be reduced by effective IT designs) are typically difficult to measure with self-reports (Johnson and Payne 1985). Brain imaging data also require fewer subjects than most studies because they use replication and produce more data per subject (Desmond and Glover 2002). Hence, in cases where only a small set of users can test potential antecedents of IS constructs, brain imaging tools can be useful complements. Therefore, brain imaging data can offer a complementary means to identify and test antecedents of IS constructs by measuring activation in selected brain areas in response to IT stimuli.

Opportunity 5: Testing Consequences of IS Constructs
NeuroIS can examine whether brain activations help predict certain important outcomes, such as decisions (system adoption) and behaviors (system use). In contrast to self-reports of behavioral intentions that could be subject to common method bias, brain data represent an objective source of measurement. While there is not a perfect relationship between brain activity and behavior because they share a probabilistic relationship, studies have shown that brain data might be good predictors of behavior compared to self-reports, by offering different information that helps explain additional variance not captured by self-reports. For example, activation in the caudate nucleus predicts if a person might act cooperatively in the future (Delgado et al. 2005), and activation in the insular cortex can predict whether a person might reject an offer (Sanfey et al. 2003). Dimoka (2010) showed that brain activations associated with trust and distrust better predict price premiums than the corresponding self-reported measures of trust and distrust. Thus, brain data can also be used for prediction, especially in cases where other measures are weak predictors. Also, brain data might be a potential alternative for IS researchers who do not rely on self-reported measures, such as IS economists and design scientists.

Opportunity 6: Inferring Temporal Ordering Among IS Constructs
Functional brain imaging tools, such as fMRI have good temporal resolution (< 1 sec) that can determine the temporal order of brain activations associated with IS constructs. For example, Cohen et al. (1997) studied the temporal dynamics of working memory to show how different brain areas can have both a complementary and a distinct role during memory tasks. Brass et al. (2005) studied the temporal order of the prefrontal and parietal cortices to show that the prefrontal cortex precedes parietal activation in cognitive control processes.

Neuroimaging studies can use a common IT stimulus (to spawn activation in several brain areas), and they can measure the temporal ordering of the resulting brain activations. Since one of the three key prerequisites of causality is temporal precedence (Zheng and Pavlou 2010), brain data can reveal temporal precedence among IS constructs, helping capture their temporal ordering and dynamics and potentially infer causal relationships. Despite the ability to infer temporal precedence with neuroimaging tools, it is important to note that brain data are based on correlation analysis that does not guarantee causality. However, tools such as transcranial magnetic stimulation that noninvasively suppresses certain brain areas can help infer causality by showing that a certain function cannot be undertaken when certain brain areas are temporarily disrupted (Miller 2008).

Opportunity 7: Challenging IS Assumptions and Enhancing IS Theories
In terms of theory development, brain imaging data might question existing IS theories and assumptions that do not correspond to the brain's circuitry. For example, Smith et al. (2002) questioned a well-known economic assumption about the independence of payoffs and outcomes. Yoon et al. (2006) challenged the literature that people make semantic judgments about people and products in the same fashion, by showing distinct brain activations when subjects make judgments for people and products. Hedgcock and Rao (2009) extended theory on trade-off aversion by showing that trade-off choice sets are associated with *higher* negative emotions. Dimoka (2010) showed that trust and distrust are independent constructs with clearly distinct neural correlates, thus refuting theories that viewed trust and distrust lying along a continuum. In sum, NeuroIS studies can shed light on whether IS theories are consistent with the brain's functionality, calling for questioning IS assumptions and strengthening of IS theories, helping build superior IS theories that correspond to the brain's functionality.[3]

Application of Research Opportunities to IS Research
Drawing upon these opportunities, we discuss how the cognitive neuroscience literature and functional brain imaging tools can help enhance research on design science and HCI (Table 4). Other opportunities for NeuroIS research are discussed in Online Appendix 2. These opportunities capture various levels of analysis, such as the individual (*technology*

[3] We should acknowledge that not all IS theories might be amenable to brain imaging studies. For example, IS theories at the organizational or strategy level might be less suitable relative to individual- or group-level theories. Also, given the constrained fMRI setting, it might not be possible to examine tasks that require excessive motor movement. Moreover, given the constraints of fMRI studies because of cost and time constraints, there might be a limit to the number of constructs.

Table 4 Application of NeuroIS Opportunities to Design Science and Human-Computer Interaction

1. **Localizing Neural Correlates of Usability:** The user's evaluation of the usability of IT artifacts may be associated with neural correlates in the brain that could be objectively captured by brain imaging tools. Usability metrics, such as effectiveness, efficiency, and user satisfaction, could be localized in the brain. Moreover, other success outcomes, such as cognitive overload and situational awareness, could be localized. Since the neural correlates of cognitive overload have been identified in the cognitive neuroscience literature, Lee et al. (2005) examined the impact of three design features on cognitive workload when coping with emergency situations in process control systems. Different types of learning can also be localized. For example, the literature focused on mental and motor learning (Nyberg et al. 2006). Also, McCrickard et al. (2003) introduced a human information processing model for testing the effectiveness of different notification systems on user interruptions, attention, and goals. Finally, Oulasvirta and Saariluoma (2006) examined the role of user interface features for coping with task interruptions in various task environments. Having localized the neural correlates of usability and other measures of system success, the corresponding brain activations can become the means for assessing the performance of IT designs and help guide the design of future IT systems.
2. **Capturing Hidden Processes**: Design science and the HCI literature emphasize conscious evaluation of IT designs, and they rarely examine hidden (e.g., unconscious, automatic, habitual) processes, which may also shape the success of IT designs. Also, emotional processes have largely been outside the toolkit of HCI researchers and design scientists; brain imaging tools can capture emotional processes, such as affect, interest, and satisfaction, which have been largely overlooked by design scientists that rely solely on cognitive responses but may help design superior IT systems.
3. **Complementing Existing Sources of Data:** Brain data can complement traditional usability studies that have relied on task analysis, focus groups, and surveys/experiments. Many design scientists do not rely on users' self-reported measures since these measures may be subject to measurement biases, such as subjectivity or social desirability bias. Brain imaging tools can overcome these limitations of self-reported measurement by enabling a direct and unbiased measurement of brain activity. Since HCI researchers often rely on behavioral metrics for evaluating IT designs (Minnery and Fine 2009), brain measures could offer an additional complementary means for assessing IT designs.
4. **IT Designs as Antecedents of Usability/System Success:** Having found the neural correlates of system success or usability, design scientists can attempt to develop and test IT artifacts that can spawn activation in these brain areas. Research on HCI is increasingly drawing upon cognitive neuroscience concepts to evaluate the design of IT artifacts (e.g., algorithms, designs, interfaces, languages) (e.g., Minnery and Fine 2009). Also, functional brain imaging tools can examine whether IT designs can activate the "usability" brain areas, helping obtain an objective assessment of whether IT designs facilitate their desired effects. For example, Spink et al. (2002) designed a multitasking model of online information search in the brain to advance the design of information retrieval tools. Moreover, having identified the brain areas associated with emotional rewards and processes, HCI researchers and design scientists could test whether IT designs are visually pleasing to users by observing their brain activations.
5. **Testing Consequences of IT Artifacts:** The brain activations associated with IT artifacts can be tested on their ability to predict favorable consequences, such as use, productivity, satisfaction, and other user behaviors. Besides, the cognitive neuroscience literature has identified major differences when users interact with computers versus humans. McCabe et al. (2001) show a significant activation in the brain only when subjects played a cooperative game with a human, but no activation when engaging with computer. Rilling et al. (2004) showed stronger brain activations when people played against humans than computers, distinguishing whether a subject played against a human or a computer. Rilling et al. also showed that participants rejected unfair offers from humans more frequently than from computers, and they cooperated with humans more frequently. These findings can have implications for design scientists to create "human-like" IT interfaces using brain activations as a measure of a more human-like IT interface.
6. **Inferring Temporal Ordering Among Brain Areas:** To better understand the design of IT artifacts, it may be useful to examine the timing of brain activations. For example, if a proposed IT design is claimed to achieve usability by being visually appealing, then brain activations should first be observed temporally in the brain area associated with visual appeal. The temporal ordering of the brain activations can also test hypotheses about the process by which IT designs affect various outcomes, such as reducing cognitive effort or achieving aesthetic design.
7. **Enhancing Design Science and HCI Theories:** The ultimate benefit of brain imaging studies would be to advance methods for developing, refining, and testing IT artifacts. The ultimate challenge would be to show that brain imaging studies can offer insights beyond what behavioral studies or existing computational models can offer. Design science and the HCI literature can take advantage of brain imaging tools to advance the design, usability, and performance of IT artifacts by having a more direct and objective relationship between the human brain and the focal IT artifact.

adoption and use), group (*virtual teams*), organizational (*information processing*), market (*e-commerce*), and societal (*cross-cultural studies*) levels. While the respondent in brain imaging studies is always the individual, brain imaging tools are not constrained by the individual level, but they may extend to other levels of analysis by relying on "hyper-scanning" (King-Casas et al. 2005) to simultaneously scan several individuals that are part of a certain group, key respondents to examine organizational or interorganizational phenomena (e.g., IS managers), consumers to examine market phenomena, or users from various cultures to examine cross-cultural differences. This is equivalent to interviews, experiments, or surveys that collect data from individuals as key respondents to make inferences about phenomena at higher levels of analysis.

We hope that the proposed example opportunities (Table 4 and Online Appendix 2) serve as a starting blueprint for IS researchers to explore other areas. For example, the literature on IT labor can draw upon the extensive cognitive neuroscience literature on rewards that has identified the brain areas responsible for the magnitude (Hsu et al. 2005), predictability (Knutson et al. 2001), and timing of rewards (McClure et al. 2004a) to devise appropriate compensation schemes for IT professionals. The IS strategy literature can also benefit by drawing upon the knowledge of how people evaluate the magnitude and probability of gains and losses to examine how IT executives make IT investments, administer portfolios of IS projects, and manage the risks of IT projects. For example, Lo and Repin (2002) examined brain data of 10 professional foreign exchange traders during a simulated market exercise while managing actual currency contracts of over $1,000,000. Such realistic studies with real-life participants in various contexts suggest that the cognitive neuroscience literature and functional brain imaging tools can shed light on multiple areas of IS research beyond those proposed in this paper.

4. Example NeuroIS Study on Technology Adoption and Use in E-commerce

A relatively simple NeuroIS example study is presented to illustrate how functional brain imaging tools (i.e., fMRI) can be used to inform the technology adoption and use in e-commerce.

4.1. Experimental Protocol, Data Analysis, and Results

We experimentally manipulated two websites—a real commercial website (Website 1) and a fictitious one (Website 2)—to differ in their functionality (usefulness) and user friendliness (ease of use). Six subjects (four male and two female) between 20 and 33 years old (mean = 24) were recruited to participate in the experiment.

The protocol had three stages (before, during, and after the fMRI session). First, before the fMRI session, the subjects were asked to browse each website for 15 minutes, aiming to purchase a certain digital camera.

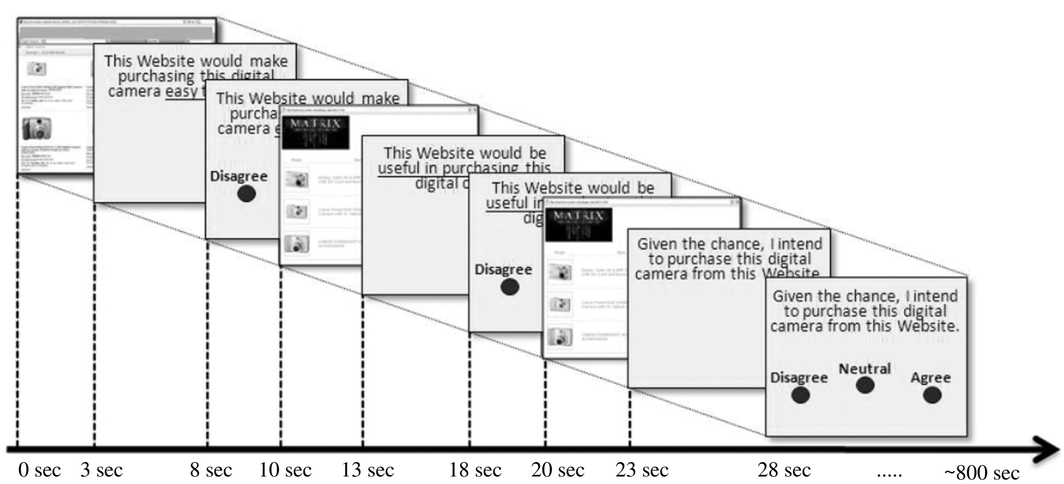
We manipulated the degree of perceived usefulness and ease of use by varying the number of products, search capabilities, product descriptions, and customer and expert reviews that describe Website 1 as a high-quality and easy-to-use website and Website 2 as a low quality, difficult-to-use website. Manipulation checks showed Website 1 to be significantly higher ($p < 0.01$) than Website 2 in terms of perceived usefulness and ease of use.

During the fMRI session, the stimuli were presented on a computerized digital projection screen placed in front of the subjects through a mirror system. The subjects were randomly shown one of the two websites for three seconds, followed by an also randomly shown measurement item on perceived usefulness, ease of use, or intentions to purchase. The measurement items were randomly intermixed to precisely target the corresponding constructs without causing halo or carry over effects. The website image aimed at directing the subjects to each website (the IT stimulus), while the measurement items were used to induce brain activation specifically for each of the focal constructs. After five seconds, the subjects were shown the anchors of a 3-point Likert-type scale below the measurement item, and were asked to select one of them (1 = Disagree; 2 = Neutral; 3 = Agree) by clicking the button of a custom-made fiberoptic device. After the subjects clicked on their choice, the next randomly selected website image and measurement item appeared (Figure 2). Ten measurement items were used based on Davis (1989), adapted for the study's e-commerce context (Pavlou 2003) for each of the three constructs and the two websites for a total of 60 ($3 \times 2 \times 10$) measurement items. Using a 3-Tesla fMRI scanner, brain data for the entire brain were acquired in a continuous time-series fashion at 5 mm-thick brain slices.

After the fMRI session, subjects were asked to respond to the exact same measurement items of the three constructs on a traditional 7-point Likert-type paper format. This step tested whether the subjects' responses during the fMRI session differed from their responses in the traditional paper format (Phan et al. 2004).

The analysis of the fMRI data was performed with the SPM2 freeware following standard procedures

Figure 2 Graphical Representation of the fMRI Protocol



(Online Appendix 3). To localize the neural correlates of each construct and minimize confounds due to visual stimuli, hand movement, and other sources of noise, we contrasted the brain activations for each construct relative to a control task for each website. All brain activations were captured when the subjects were processing each measurement item (before posting their response). For each construct, the resulting statistical parametric maps display the z-value of each voxel (3D pixel) ($p < 0.05$ threshold). Then, we correlated each subjects' level of brain activation (z-scores) for each construct with the subjects' responses to each construct's self-reported measurement items (during the fMRI session), aiming to test whether each subject's level of agreement with the measurement items for each construct is associated with a higher level of brain activation.

The results are graphically shown in Figure 3 using a color-coded significance bar and discussed in Table 5.

4.2. Implications for Technology Adoption and Use in E-commerce

The study of the technology adoption and use constructs in the e-commerce context with brain data illustrates many of the proposed seven opportunities for the potential of cognitive neuroscience for IS research.

First, identifying the neural correlates of the TAM constructs informs their nature and dimensionality. Perceived usefulness is associated with brain areas associated with utility (caudate nucleus and anterior cingulate cortex) and potential for loss (insular cortex). The caudate nucleus is innervated by dopamine neurons that are activated when one enjoys a large reward (McClure et al. 2004a), while the anterior cingulate cortex is the "executive" branch of the limbic system that is activated in the anticipation of rewards for decision making (Delgado et al. 2005). This implies that high levels of perceived usefulness may actually be a multidimensional construct with at least two dimensions, one associated with the *magnitude* of the reward and one with the *anticipation* of the expected reward. In contrast, the low level of usefulness corresponds to a distinct brain area associated with loss, implying fear of negative utility. Perceived ease of use is mapped on the DLPFC, a brain area linked to cognitive effort and working memory. The activation in a single brain area supports the view of perceived ease of use in the TAM literature as a unidimensional construct.

Second, this study shows how neuroimaging studies can identify hidden processes that might be difficult to capture with self-reported studies. Perceived usefulness is associated with brain areas in the limbic system (caudate nucleus, anterior cingulate cortex, insular cortex) that are associated with rewards, utility, and loss (e.g., Delgado et al. 2005). While usefulness has been viewed as a purely cognitive construct in the literature (Davis 1989), its neural correlates imply links to the "emotional" brain, such as the anterior cingulate cortex that is considered an "interface" area for integrating emotional tasks with cognitive demands (Phan et al. 2002). This suggests that

Figure 3 Areas of Brain Activation for Perceived Usefulness, Ease of Use, and Intentions

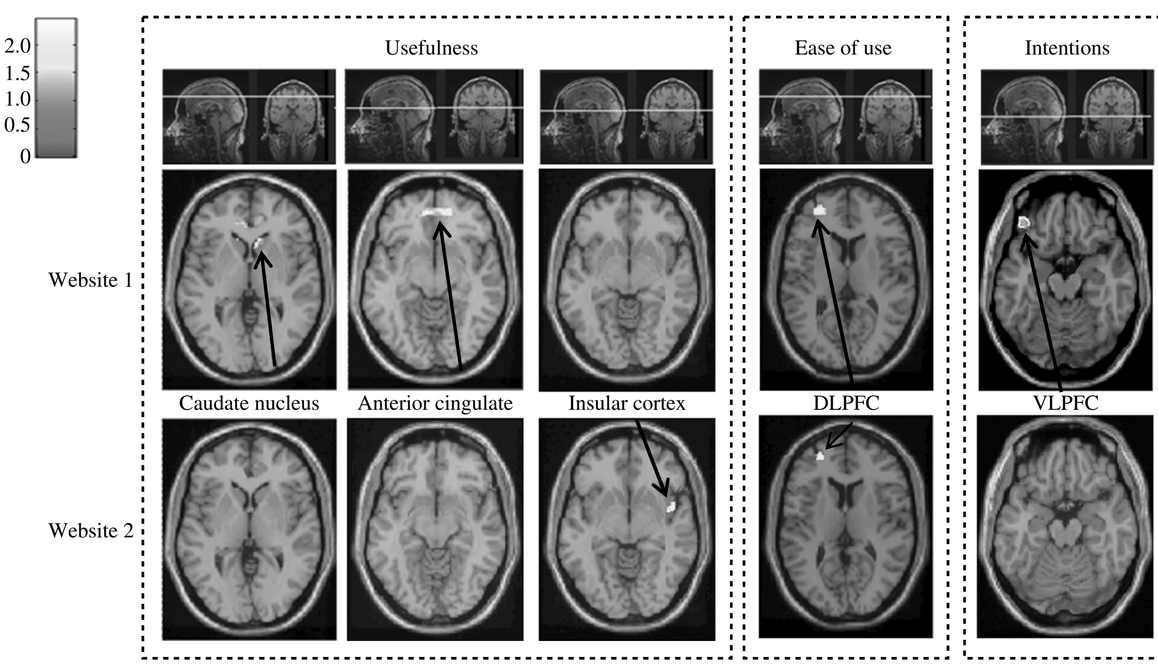


Table 5 Results for Perceived Usefulness, Ease of Use, and Intentions

Perceived usefulness: Perceived usefulness for Website 1 (behavioral data: $\mu = 2.92$, 3 = Strongly Agree) activated the *caudate nucleus* (z-value = 1.89, $p < 0.05$) and the *anterior cingulate cortex* (z-value = 2.19, $p < 0.05$). Usefulness for Website 2 ($\mu = 1.56$, 1 = Strongly Disagree) activated the *insular cortex* (z-value = 2.93, $p < 0.01$). The caudate nucleus is activated by the *magnitude* of an anticipated reward (Hsu et al. 2005), while the anterior cingulate cortex is activated by the *anticipation* of a reward (Bush et al. 2002). The insular cortex is activated by intense emotions and fear of loss (Wicker et al. 2003). The level of brain activation in the anterior cingulate ($r = 0.69$, $p < 0.001$) and caudate nucleus ($r = 0.59$, $p < 0.001$) was highly correlated with the self-reported responses to the self-reported measurement items of perceived usefulness for the two websites. The level of brain activation in the insular cortex was negatively correlated ($r = -0.57$, $p < 0.01$) with the subjects' self-reported responses to the perceived usefulness items. Finally, the self-reported responses to the perceived usefulness items during and after the fMRI session are highly correlated ($r = 0.92$, $p < 0.001$).

Perceived ease of use: Perceived ease of use significantly ($p < 0.05$) activated the *dorsolateral prefrontal cortex* (DLPFC) for both websites. The DLPFC is associated with cognitive effort (Rypma and D'Esposito 1999), working memory (Braver et al. 1997), and problem solving (Stuss et al. 2000). The level of DLPFC activation for Website 1 (z-level = 3.01, $p < 0.01$) is significantly ($p < 0.01$) higher than that of Website 2 (z-level = 2.36, $p < 0.05$), which is consistent with the self-reported responses for Website 1 ($\mu = 2.90$) versus Website 2 ($\mu = 2.35$) ($p < 0.05$). The level of brain activation in the DLPFC was significantly correlated ($r = 0.58$, $p < 0.01$) with the self-reported responses to the measurement items of perceived ease of use. Furthermore, the self-reported responses on perceived ease of use during and after the fMRI session were also highly correlated ($r = 0.90$, $p < 0.001$).

Intentions: Intentions to purchase from Website 1 ($\mu = 2.98$) activated the *ventrolateral prefrontal cortex* (VLPFC) (z-value = 2.63, $p < 0.01$), while intentions to purchase from Website 2 ($\mu = 1.03$) activated the *left putamen* (z-value = 1.85, $p < 0.05$). The VLPFC relates to intentions (Dove et al. 2008), while the left putamen is activated when a person realizes an error in her reward prediction (McClure et al. 2003). The self-reported responses during and after the fMRI session were also highly correlated ($r = 0.93$, $p < 0.001$).

neural correlates of perceived usefulness are not in the brain's purely cognitive areas (i.e., prefrontal cortex), as one might expect based on cognitive instrumental theorizing in the TAM literature. The localization of intentions in the VLPFC and left putamen could suggest that behavioral intentions might also have an emotional element that has been largely ignored by the intentions literature (e.g., TAM, TRA, TPB). In contrast to the literature that has focused on the cognitive component of behavioral intentions, this functional brain imaging study implies that intentions might also have a "hidden" emotional component.

Third, in terms of complementing existing data sources with brain imaging data, the results show that the self-reported responses to the TAM constructs are significantly correlated with the level of brain activations that are induced by the underlying IT stimuli (the two manipulated websites that differ in their functionality and user friendliness). This suggests that the measurement items for the TAM constructs closely correspond to brain activations associated with utility (usefulness), cognitive effort (ease of use), and cognitive intentions (intentions to purchase), implying the validity of the TAM scales (Davis 1989). These results are consistent with Lieberman et al. (2009), who posit that it is possible to have very high brain-behavior correlations. Still, the finding that distinct areas of the brain are activated for low versus high level of perceived usefulness and intentions might imply that these two constructs might not be necessarily linear and continuous. These findings could challenge the underlying assumption in the IS literature that the measurement of perceived usefulness and intentions is linear and continuous, implying that brain data might call for new measurement scales that better correspond to the brain's functionality, which seems to exhibit potential nonlinearities and discontinuities.

Fourth, this study shows the possibility of examining antecedents of perceived usefulness and ease of use. The manipulation of two websites that differ on their usefulness and ease of use acted as the IT stimulus to activate the brain areas that are associated with the TAM constructs. These findings could have implications for identifying additional, less obvious antecedents of the TAM constructs, such as new IT systems and prototypes. The neural correlates of the two TAM constructs—usefulness and ease of use—can test the utility and user friendliness of different IT systems, and they could be particularly useful for design science and HCI research.

Opportunities 5 and 6 (consequences and temporal order of IS constructs) were not examined in this study. In terms of challenging the IS literature (Opportunity 7), while usefulness is theorized to correspond to higher-order executive goals (Davis 1989), there is no brain activation in the prefrontal cortex that is responsible for cognitive goal attainment (Newman-Norlund et al. 2007).

Instead, the neural correlates of usefulness point out the limbic system, a more emotional part of the brain that is related to rewards and utility. While the anterior cingulate cortex is the most "executive" part of the limbic system that is often viewed as a "hub" that integrates the emotional and cognitive brain areas, it is interesting to show that usefulness resides in the limbic system and does not have neural correlates in the prefrontal cortex. This finding is in line with the cognitive neuroscience literature that has established the superordinate role of emotions for regulating cognitive mechanisms of executive control (e.g., Hsu et al. 2005, Pessoa 2008). Perhaps the study's particular context of website use (versus system use in a classical organizational context) is more hedonic than utilitarian in nature, and it thus triggers the less cognitive parts of the brain. Moreover, because using a website for purchasing implies *immediate* rewards, the perceived usefulness for website use for purchasing might be related to more emotional brain areas, such as the limbic system (McClure et al. 2004a). Perhaps system use in classic organizational environments would be associated with *less immediate* rewards, and it might activate more cognitive brain areas, such as the lateral prefrontal cortex (McClure et al. 2004a). While future research is still needed to examine the neural correlates of perceived usefulness and intentions in the context of utilitarian system use in classical organizational environments, before making solid conclusions about the neural correlates of perceived usefulness and intentions, these neuroimaging results point out some interesting findings that might challenge the IS literature about the underlying nature of these two constructs.

Similarly, while ease of use is theorized as a lower-level goal in the goal hierarchy (Davis 1989), it is still linked to the brain's executive control processing center (DLPFC), which is associated with working memory, problem solving, and executive goals. Besides, there is no significant activation observed in areas associated with any emotional (e.g., anger, frustration) or unconscious (e.g., habit, automaticity) processes. These findings might imply that, at least for the present context, perceived ease of use is a higher-order goal that is conscious and cognitive. While this study did not examine the temporal dynamics of perceived ease of use and usefulness to draw inferences about their temporal ordering, given that emotional processes typically precede cognitive ones (Pessoa 2008), it would be interesting to show whether ease of use actually precedes usefulness (or vice versa).

In summary, while more studies are needed to make definite conclusions about the nature, relationships, and role of the TAM constructs, these findings underscore the potential of NeuroIS to question and extend IS theories.

5. General Discussion

5.1. Current Challenges in Cognitive Neuroscience

Despite the proposed potential of cognitive neuroscience for IS research, please note that it is not the panacea to all IS research problems, and that brain imaging data are not unequivocally superior to existing IS data. Indeed, there are several challenges and inherent limitations of brain imaging tools that are subject of discussion and active research in the cognitive neuroscience literature (e.g., Logothetis 2008, Miller 2008).

Cost and Accessibility: The most common criticism of brain imaging tools, particularly fMRI, is their cost and accessibility. This is because the typical cost of using an fMRI scanner (including miscellaneous costs) is about \$200 to \$500/hour. However, given the accuracy of brain data, the required number of subjects is small (Desmond and Glover 2002), and 10 to 15 subjects are typically needed for a study. Since one to two subjects can be scanned in one hour, the total cost of an fMRI study is manageable. However, as Camerer et al. (2004) explain, judgment of cost is a subjective issue that is best answered by the entity paying for the research relative to its potential value. In terms of the analysis of imaging data, the standard SPM software is free, and a standard computer can address most issues of data storage and processing. In terms of accessibility, many universities and hospitals now have fMRI scanners and other brain imaging tools that are available for research. Finally, another limitation is the constrained environment of the fMRI scanner where subjects have limited movement. This is why it is recommended to replicate the fMRI study in a traditional setting to compare the behavioral responses (Yoon et al. 2009). Evidence suggests that subjects respond similarly within and outside the fMRI scanner (Dimoka 2010, Phan et al. 2004), as our results also attest, implying external validity.

Interpretation of Results: There is also active research on the interpretation of brain imaging results (Logothetis 2008), particularly in terms of localizing brain activity in response to mental processes.

First, a naive interpretation is a one-to-one mapping between a brain area and a mental process; simply put, there is a many-to-many correspondence between brain areas and mental processes, and inferring that activity in a brain area *necessitates* the existence of a certain process (termed reverse inference) could be problematic (Poldrack 2006). Region-of-interest analysis is one mechanism used to address this problem (Poldrack 2007). Future IS research could explore the many-to-many correspondence between brain activity and IS constructs, aiming to develop a taxonomy of the neural correlates of IS constructs, similar to what we have in Table 3.

Second, the literature has generally adopted a modular view of brain activity by focusing on localized blood flows. However, because a mental process is often associated with several brain areas, the objective is to capture the networked nature of the brain's functionality by modeling the pattern of co-activation among brain networks (e.g., Aron 2008). For example, diffusion spectrum imaging (Hagmann et al. 2008) can help examine the interconnectivity and temporal sequences among brain areas. Moreover, pattern classification methods can identify patterns of brain areas that predict a certain mental process (Kriegeskorte et al. 2006). Finally, clustering methods were also proposed to identify functionally connected brain areas (Stanberry et al. 2008). Nonetheless, today's brain imaging tools that focus on physical processes associated with blood flow are still far away from fully capturing all complex phenomena associated with conscious and unconscious cognition.

Third, each brain imaging tool has its own spatial and temporal resolution that determines its precision and sensitivity; moreover, brain imaging tools have additional idiosyncrasies, such as PET that uses radioactive markers. However, the resolution of these tools is continuously enhanced by advances in imaging technology. For example, there are currently 9-Tesla fMRI scanners cleared for human use that promise superb resolution.

Individual Variation and Plasticity: To account for cortical differences across people, the brain images must be normalized to a template brain (Online Appendix 3). Besides structural differences, the brain's functionality and organization are similar across people, and the goal is to derive generalizable inferences about the aggregate population by modeling various sources of intersubject variability as confounds (Holmes and Friston 1998). Accordingly, while the analysis of brain data starts at the individual level and concludes with aggregate results, because a group-level analysis requires spatial smoothing that reduces spatial resolution (Price and Friston 2005), there is active research on modeling and accounting for intersubject variability (e.g., Mechelli et al. 2002) to enhance the generalizability of group-level analysis (e.g., Thirion et al. 2007), at least across healthy subjects.

While brain functionality is similar across normal, right-handed subjects, brain injury might cause plasticity (reorganization of the brain's functionality, neural pathways, and organization). This might result in different functionality across people because healthy brain areas assume the function of injured areas (termed *degeneracy*) (Price and Friston 2005). Therefore, most studies generalize findings across healthy—and not injured—subjects.

Manipulation and Ethics: Cognitive neuroscience and specifically neuromarketing have been attacked for their alleged potential to manipulate people in responding to advertising and products. While brain imaging tools help better understand consumer behavior, they can only *observe* brain activity, not manipulate behavior. Still, brain imaging tools must be governed by strict guidelines that govern ethical research (Farah 2002), and IS researchers must always follow strict rules for ethical research, irrespective of the tools at their discretion.

5.2. Can We Afford to Treat the Human Brain as a "Black Box"?

Despite these challenges, we argue that IS researchers cannot treat the brain as a "black box," and propose that cognitive neuroscience can enhance IS research from a *descriptive*, *predictive*, and *prescriptive* perspective.

Implications for Enhancing the Descriptive Power of IS Theories

Rich knowledge of the underlying brain activity can guide theory selection and test competing theories. For example, if two competing theories on the process by which an IT stimulus (e.g., a trust-building seal) influences a certain behavior (purchasing) suggest different mediating variables (e.g., trust, risk, or both), a NeuroIS study can identify which of these two variables is the most likely mediator based on brain activations. Since the brain areas related to trust (caudate nucleus) and risk (nucleus accumbens) have been identified in the cognitive neuroscience literature, a NeuroIS study can help identify whether the trust-building seal activates the caudate nucleus or the nucleus accumbens (or both), plus their level of activation. In doing so, a NeuroIS study can identify the most appropriate mediator(s) that maximize the model's descriptive power.

Brain imaging tools can help capture variables that might have been difficult to capture, thus helping include missing variables and mitigating *omitted variable bias*. For instance, if a trust-building seal activates other areas beyond the caudate nucleus or nucleus accumbens, it might be an indication that other mediators might exist. Also, if a given area of brain activation implies the existence of a given variable, the cognitive neuroscience literature might help identify such a variable to enhance a model's descriptive power. For example, if a trust-building seal spawns brain activation in the insular cortex (associated with fear of loss or ambiguity), this finding might imply that the subjects either believe that the seal could be fraudulent or they might be confused about the seal.

In terms of variable selection, brain imaging tools can also help guide if a variable should exist in a model; if the expected brain activation associated with a certain variable is not observed, this variable might be excluded from the model. For example, if a trust-building stimulus does not activate the nucleus accumbens, risk may be excluded. Furthermore, if there is no caudate nucleus activation, this could imply that trust is not engendered. However, if both activations are observed, their timing can shed light on whether trust precedes risk, implying that the seal first builds trust, which is then used to reduce risk perceptions and encourage a trusting behavior.

While many constructs that could be of interest to IS research have already been examined in the cognitive neuroscience literature (Table 3), many IS-specific constructs that have a particular meaning in the IS literature (e.g., computer self-efficacy, Internet anxiety) would probably require new brain imaging studies to identify their brain localization. In doing so, IS researchers could start contributing to the rapidly growing cognitive neuroscience literature by adding IS constructs to the existing body of existing mental processes.

Finally, brain imaging tools can help with measurement issues (Bernheim 2008). For example, several latent variables that cannot be measured objectively due to measurement biases, such as trust, utility, and cognitive overload, can be measured more reliably with brain data, enabling a new wave of IS research.

Implications for Enhancing the Predictive Power of IS Theories

Since the accurate prediction of behavior is very important for IS research, from a predictive standpoint, can brain activation better predict behavior than the underlying IT stimuli? Since brain data are objective and do not suffer from measurement biases, they might be more reliable and stable predictors than perceptual data (Bernheim 2008). For example, brain data might be able to better predict the success of an IT prototype compared to self-reports, plus a smaller sample size might be enough. Since brain activations can be quantified with continuous statistical measures (z-scores), they can be used in predictive regression-type models, either to compare across various brain activations to compare brain activations along with other potential variables. This can test whether the brain data can better predict human behavior than existing behavioral predictors.

Implications for Enhancing the Prescriptive/Design Power of IS Theories

NeuroIS can also help IS researchers design better IT systems and tools, such as designing useful and user friendly systems that facilitate adoption, use, and enhanced productivity. Rather than relying on perceptual evaluations of IT artifacts, the brain areas associated with the desired effects can be used as an objective dependent variable in which the IT artifacts will be designed to affect. For example, the areas associated with perceived usefulness (caudate nucleus and anterior cingulate cortex) and ease of use (DLPFC) can be used as the basis for designing superior IT systems: the systems would facilitate technology adoption and use by enhancing the magnitude and probability of the utility derived by the system and reducing the system's cognitive overload. In e-commerce, the areas linked to intentions to purchase (e.g., VLPFC) can be used as dependent variables for designing superior websites that aim to encourage consumers to purchase online. In sum, IS research can rely on brain data to design IT systems that facilitate favorable behaviors by people, organizations, and markets.

5.3. Conclusion

Despite the potential of cognitive neuroscience for the social sciences, IS researchers might choose to ignore its potential for IS research. However, IS research has long drawn upon leading reference disciplines to inform IS phenomena, and ignoring the cognitive neuroscience discipline IS could be a disservice to the field. This paper's basic premise is that the cognitive neuroscience literature and brain imaging tools can open up new research directions that could accelerate our progress toward understanding the increasingly complex interplay between IT and information processing, decision-making, and behavior by offering a novel complementary scientific foundation. After all, a new scientific tool is most useful when it is complemented by existing theories, methodologies, and data (Caccioppo et al. 2008). We hope that the cognitive neuroscience literature and brain imaging tools would trigger a revolution in IS research to fundamentally strengthen the IS discipline and help spawn novel and cutting-edge conceptual foundations for enhancing IS theories. Simply put, it is hard to believe that a better understanding of the brain's functionality will not lead to superior IS theories.

6. Electronic Companion

An electronic companion to this paper is available as part of the online version that can be found at http://isr.journal.informs.org/.

Acknowledgments

The authors thank Izak Benbasat, Nanda Kumar, Vanessa Liu, Munir Mandviwalla, and Yair Wand for comments on earlier versions of this manuscript. The study also benefited from feedback during seminar presentations at the 2007 International Conference on Information Systems (ICIS), the 2007 Workshop on Information Systems Economics (WISE), City University of Hong Kong, Temple University, University of British Columbia, and University of California, Irvine. Fred D. Davis's work on this article was supported by the Service Systems Management and Engineering Department of Sogang Business School, which is funded by Korean Research Foundation World Class University Project R32-20002.

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