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Using Psycho-physiological Interaction Analysis with fMRI Data in IS Research: A Guideline

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Abstract:

The integration of neuroscientific methods in Information Systems (IS) research to better understand how the brain interacts with IS-relevant context has gained in importance. Many papers that highlight the potential of neuroIS and that discuss methodological issues associated with using functional brain imaging already exist. However, neuroIS researchers have to keep in mind that the emergence of complex mental processes such as trust in IS contexts is based on activity in a network of brain regions rather than on activity in one area alone. Accordingly, we introduce psycho-physiological interaction (PPI) analysis, a technique that one can use to analyze fMRI data. Specifically, we review how one can conduct PPI analysis, provide a concrete research example, and show how this analysis can inform IS trust research. Thus, we introduce neuroIS researchers working in the domain of functional brain imaging to advanced fMRI analyses methods and show, based on the example of trust, how these methods can enhance our understanding of the nature of IS constructs.

Keywords: Behavioral Science, Cognition/Cognitive Science, Data Analysis, fMRI, NeuroIS, Neuroscientific Research, Psycho-Physiological Interaction Analysis, Trust, Trustworthiness.

1　Introduction

Papers in the information systems (IS) literature have revealed the growing importance of integrating neuroscientific and psychophysiological methods and theories into IS research to better understand how the brain, and human neurophysiology in general, operate in IS contexts (e.g., Dimoka, Pavlou, & Davis, 2011; Loos et al., 2010; Riedl et al., 2010a; Riedl, Davis, & Hevner, 2014a). This kind of knowledge about the brain is important because neurophysiological processes influence human perceptions, preferences, beliefs, attitudes, behavioral intentions, and, ultimately, actual behavior (Cacioppo, Tassinary, & Berntson, 2007; Glimcher & Fehr, 2013; Yoon et al., 2012). Various conceptual papers have defined the neuroIS field and identified promising research areas, but they have also revealed potential challenges (Dimoka et al., 2012; Riedl et al., 2010a; 2014a; vom Brocke & Liang, 2014). Furthermore, empirical neuroIS studies published in the last several years show that functional magnetic resonance imaging (fMRI) is an important tool in neuroIS research. Several IS top journals have published fMRI papers, including *MIS Quarterly* (Dimoka, 2010; Riedl, Hubert, & Kenning 2010b), the *Journal of Management Information Systems* (Riedl, Mohr, Kenning, Davis, & Heekeren, 2014b), and the *Journal of the Association for Information Systems* (Warkentin, Walden, Johnston, & Straub, 2016). Also, the proceedings of the International Conference on Information Systems have published several fMRI papers (e.g., Anderson, Vance, Kirwan, Eargle, & Howard, 2014; Dimoka & Davis, 2008; Kopton, Sommer, Winkelmann, Riedl, & Kenning, 2013; Riedl, Mohr, Kenning, Davis, & Heekeren, 2011). Moreover, Riedl and Leger (2016, chapter 4) recently analyzed neuroIS research and found that 13 out of the 85 (15%) papers they identified adopted fMRI.

FMRI is a neuroimaging method that measures brain activity based on related changes in blood flow or, more specifically, the blood-oxygen-level dependent (BOLD) contrast (Huettel, Song, & McCarthy, 2009). Despite its relatively high cost of application (Ariely & Berns, 2010), this tool has become an essential research method for, among others, cognitive neuroscientists and neuroIS scholars. A primary advantage of fMRI is its ability to localize brain activity at a precision level of a millimeter simultaneous to stimulus presentation. Thus, fMRI allows one to observe various effects of IS stimulus perception (e.g., a user interface) on neural processing in multiple brain regions (Huettel et al., 2009).

How properly one applies methods and corresponding statistical computations largely determines the quality of research results from fMRI studies. Thus, we need guidelines and methodical discussions about how to collect and analyze data for such studies (Dimoka, 2012; Riedl, Davis, & Hevner, 2014a). Because the neuroscience literature does not consider the idiosyncrasies of IS research, guidelines and methods papers on specific neuroscientific tools and their application in the IS domain fulfill an important "service function" in the IS field. Examples for such guidelines and methods papers include Dimoka's(2012) paper on fMRI, Müller-Putz, Riedl, and Wriessnegger's (2015) paper on the application of electroencephalography (EEG) in IS research, or Gefen, Ayaz, and Onaral's (2014) paper on the application of functional near-infrared spectroscopy (fNIRS) in IS research. Moreover, the neuroIS field urgently needs methodological discussions because they create a common understanding of methods and measurements among editors, reviewers, and authors (Riedl et al., 2014a; vom Brocke & Liang, 2014). A lack of serious discourse on neuroIS methodology hampers this subfield's development and leaves its contribution to IS research in general unclear and in doubt.

Against this background, and considering the rapid methodological advancements in brain research, IS research must consider proper conceptualization of the functioning of the human brain (Friston, Baojuan, Duanizeau, & Stephan, 2011), which holds particularly true if one considers that complex cognitive and affective processes in IS contexts (e.g., trust or decision making; for a list of constructs of interest to IS research, see Dimoka et al., 2011, p. 691) are often based on activity in a network of brain regions (functional integration) and not on activity in only one or a limited number of areas (functional specialization) (see Figure 1; for a general discussion, see also Friston, 2002; Friston et al., 2011; Hare, Camerer, Knoepfle, O`Doherty, & Rangel, 2010; Heim, Friederici, Schiller, Rueschemeyer, & Amunts, 2009; Penny, Stephan, Mechelli, & Friston, 2004).
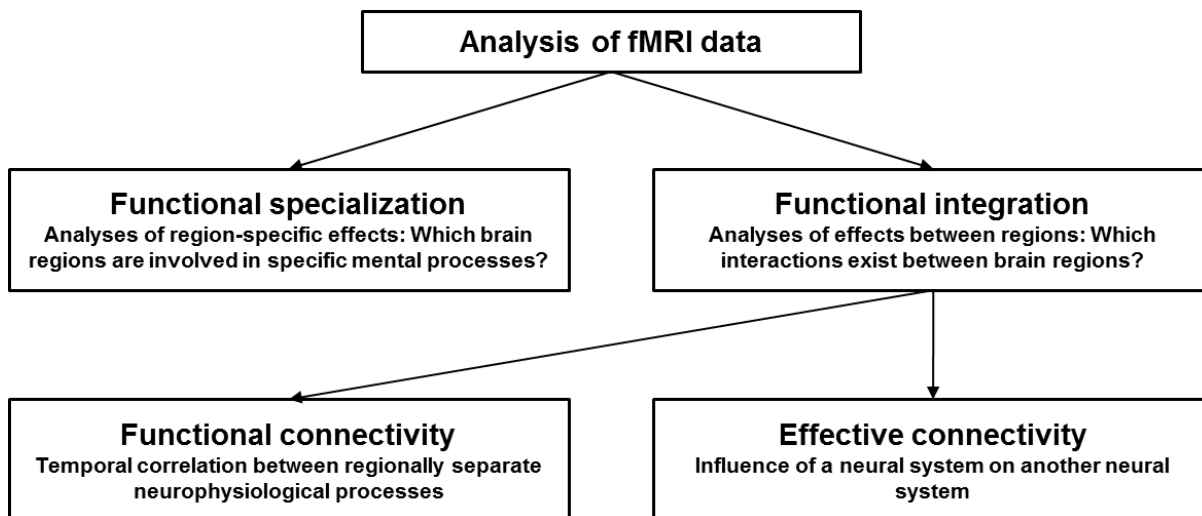
Figure 1. Analysis Categories for fMRI Data (Adapted from Friston, 1994, p. 58)

However, fMRI data analyses in contemporary neuroIS studies have not yet considered the idea of functional integration to analyze effects between brain regions. Currently, these studies usually apply contrast-based techniques or parametric modulations to statistically analyze the fMRI data (functional specialization). This approach does not lead to irrelevant or even incorrect research results because of its necessary exploratory nature (i.e., to answer the question: what regions are activated?), but functional specialization is often only a first step in fMRI data analysis, especially if one is interested in the temporal and causal interdependencies between different regions to reveal the causal mechanisms that underlie the formation of perceptions, preferences, beliefs, attitudes, behavioral intentions, and actual behavior (Cacioppo et al., 2007). This type of brain data analysis (functional integration) is referred to as correlation and/or connectivity analyses (e.g., see Andersen, Gash, & Avison, 1999; Baumgartner et al., 2000; Calhoun, Adali, Pearlson, & Pekar, 2001; Friston, 2009; Marreiros, Kiebel, & Friston, 2008; McKeown & Sejnowski, 1998; Penny et al., 2010; Stephan, Penny, Marshall, Fink, & Friston, 2005; Stephan et al., 2008; Stephan et al., 2010).

Accordingly, in this paper, we focus on informing neuroIS researchers about recent developments in research methodology for analyzing brain imaging data and, thereby, contribute to the development of a neuroIS research methodology (Riedl et al., 2014a). To date, publications in neuroIS research often only analyze the activity of individual brain areas (e.g., which brain areas' activity increases or decreases during a behavioral task). From a neurophysiological standpoint, O´Reilly, Woolrich, Behrens, Smith, and Johansen-Berg (2012, p. 704) write about functional localization and integration as follows:

> *Yet a major strength of functional imaging as a method is that it allows researchers to observe activity in networks of areas simultaneously and therefore as well as investigating functional localization (which areas are active during a task) it is possible to use functional imaging to probe functional interactions between brain areas.*

To introduce the idea of functional integration to IS research, we present one particular type of functional connectivity analysis: psycho-physiological interaction (PPI) analysis, which represents not only the most popular technique in the neurophysiological literature at present (O'Reilly et al., 2012) but also a method that could contribute to the development of neuroIS research.

To better assess the contribution, imagine the following hypothetical example from O'Reilly et al. (2012) that we modified and transferred to an IS context: imagine someone conducted an experiment in which participants navigated a route through a 3D virtual reality supermarket[1] to order their weekly grocery supplies while a researcher measured their brain activity with fMRI. The researcher contrasted this navigation condition with a control condition in which participants travelled passively through a similar supermarket (i.e., a virtual shopping assistant that directs them to the products they bought in the past guided them). Now imagine that, when analyzing the data, the researcher found that the prefrontal cortex

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[1] It appears that the information processing mechanisms of 3D virtual environments constitute an interesting research phenomenon with regard to many IS relevant constructs (e.g., Nah, Eschenbrenner, & De Wester, 2011).

and hippocampus were both more active during the navigation condition than during the passive control condition. Faced with these results and based on current analyses that are of a correlational nature, the researcher might come up with at least two possible interpretations. First, the prefrontal cortex and hippocampus were both independently active in the navigation condition (say, because navigation requires planning, which involves the prefrontal cortex, and because navigation requires spatial information, which is related to the hippocampus). Second, the prefrontal cortex and hippocampus interactively work together in navigation—eventually a "top-down" signal from the prefrontal cortex causes retrieval of information in the hippocampus, which is then passed back to the prefrontal cortex). If the two active areas interact during navigation, one might expect their activity to be more strongly related during navigation than during the passive supermarket travel condition. In this situation, PPI analysis is useful: for a given "seed" region (i.e., a region of interest) such as the hippocampus in this case, PPI analysis essentially tells one which voxels, across the whole brain, increase their relationship with (strength of regression on) that seed region during the task of interest. In the supermarket navigation task, the use PPI could help one to distinguish between the two interpretations by clarifying which areas increased their relationship with the hippocampus during navigation as opposed to passive virtual supermarket travel.

Statistically, the PPI analysis method   is a multiple regression analysis with moderator variables (see Banks, Eddy, Angstadt, Nathan, & Phan, 2007; Friston et al., 1997; Gitelman, Penny, Ashburner, & Friston, 2003; McLaren, Ries, Xu, & Johnson, 2012; White & Alkire, 2003; Williams et al., 2006). Building on a simple bilinear model that characterizes the influence that a specific brain region has on another region that depends on a cognitive context or experimental condition (consider the supermarket navigation example again: active condition versus passive condition), PPI is an explorative method to determine effects between regions. In this regard, PPI does not demand an a priori research model and does not make an inference about the direction of information flow (i.e., causality) (Banks et al., 2007; Friston et al., 1997; Gitelman et al., 2003; McLaren et al., 2012). With regard to experimental designs used in neuroIS research, PPI is well suited and relevant for all IS research questions when one is interested in the moderator effect of task context on interactions between brain regions.

In Section 2, based on an empirical example and a previously used data set (published in Riedl et al., 2010b), we describe how to apply a PPI analysis to better capture the complex functioning of the human brain in IS research studies. Furthermore, we discuss and outline implications for future developments in the neuroIS field.

2   The Application and Value of Psycho-physiological Interaction Analysis of fMRI Data in IS Research: An Empirical Example

In this section, we introduce the method of PPI analysis to neuroIS research using data from an fMRI study published in *MIS Quarterly* (Riedl et al., 2010b). We concentrate on the neural correlates of trust in online settings because this topic is important for IS research (Ba & Pavlou, 2002; Gefen, Benbasat, & Pavlou, 2003; Gefen, Karahanna, & Straub, 2008; Kim & Benbasat, 2006; McKnight, Choudhury, & Kacmar, 2002; Pavlou & Gefen, 2004).

2.1   Trust in Online Settings and Neurobiological Evidence

Trust, especially in complex, uncertain decision making situations, is a critical factor for successful social and economic interactions between different actors (e.g., Gefen et al., 2003, McKnight & Chervany, 1996; McKnight, Cummings, & Chervany, 1998). Trust has the crucial function of reducing social complexity and risk (Gefen et al., 2003; Gefen & Pavlou, 2012; Nicolaou & McKnight, 2006). To better understand how trust evolves in certain situations, neuroscientific studies have identified various brain regions associated with trust (Baumgartner, Heinrichs, Vonlanthen, Fischbacher, & Fehr, 2008; Delgado, Frank, & Phelps, 2005; Heekeren, Marrett, Ruff, Bandettini, & Ungerleider, 2006; King-Casas et al., 2005; Krueger et al., 2007; Winston, Strange, O´Doherty, & Dolan, 2002; for an overview, see Riedl & Javor, 2012). Also, neuroIS studies have identified several brain regions related to trust in online settings (Dimoka, 2010; Kopton et al., 2013; Riedl et al., 2010b; 2014b). Table A1 reviews fMRI studies in the trust domain and corresponding neural correlates as prior neuroscience and neuroIS studies have identified. The identification of brain areas (illustrated in bold in Appendix A, Table A1) is of particular importance (Plassmann & Weber, 2015), especially for the analyses steps of PPI that we detail in Sections 2.3.

2.2   Preliminaries: Data Set, Experimental Setup, and Details for Data Acquisition

We used a data set from a published fMRI study (Riedl et al., 2010b) to demonstrate the potential of PPI analysis (Friston, Harrison, & Penny, 2003; Stephan et al., 2010) for IS research[2]. In this way, our study broadens the methodological focus of neuroIS research and deepens the theoretical understanding of interdependencies between brain regions related to trust processes.

2.2.1   Participants

Ten male and ten female healthy, right-handed subjects participated in the Riedl et al. (2010b) fMRI study (mean age = 31.8 years, SD = 1.73, range = [30, 35]). They found no gender differences with respect to age (t(18) = -1.61, p = .125) and applied standard exclusion criteria for MR examinations (Savoy, 2005). All participants provided written informed consent prior to the scanning sessions. For their participation, all subjects received €20 in cash and one of the USB flash drives (selected randomly) that the authors used as stimulus material. Furthermore, to avoid potential confounding effects, Riedl et al. (2010b) measured general trust level (according to Rotter, 1967: 25 items, five-point Likert scale with 1 = "totally disagree" to 5 = "totally agree"; $M_{general\_trust}$ = 65.6, SD = 8.16, range = [25,125]), participants familiarity with the Internet (measured by duration of Internet usage per week in hours) ($M_{Internet/week}$ = 12.55, SD = 7.46), duration of Internet usage overall (in months) ($M_{Internet/overall}$ = 92.15, SD = 48.49), duration of eBay affinity overall (in months) (M_{ebay_usage} = 44.72, SD = 32.3), average value of successful auctions (in €) ($M_{auction}$ = 38.11, SD = 60.56), experience with and attitude toward eBay (five-point Likert scale with 1 = "extremely positive" to 5 = "extremely negative"; $M_{attitude}$ = 2.55, SD = 0.07; $M_{experience}$ = 2.45, SD = 0.51), and the importance of USB flash drives for their daily lives (five-point Likert scale with 1 = "totally disagree" to 5 = "totally agree"; $M_{importance}$ = 3.45, SD = 1.27).

2.2.2   Stimulus Material

Riedl et al. (2010b) developed their stimulus material (eBay product offer websites) based on Toulmin's model of argumentation (Toulmin, 1958). In essence, Toulmin's (1958) model proposes a layout containing four interrelated components for analyzing arguments: 1) claim, 2) data, 3) backing, and 4) rebuttal. Organizing around these components, Riedl et al. developed and pretested 104 stimuli (eBay websites) and chose 30 eBay offers for the main fMRI study (see Riedl et al. 2010b for selection process). In accordance with Riedl et al. (2010b), we used the given stimulus material with regard to five trustworthiness classes (A = "no description", B = "claim only", C = "claim+data", D = "claim+data+backing", E = "claim+data+backing+rebuttal") and expected an increase in trustworthiness evaluations from class A to class D followed by a decrease from class D to class E (according to Toulmin, 1958; see also Riedl et al., 2010b for details) (see Figure 2).
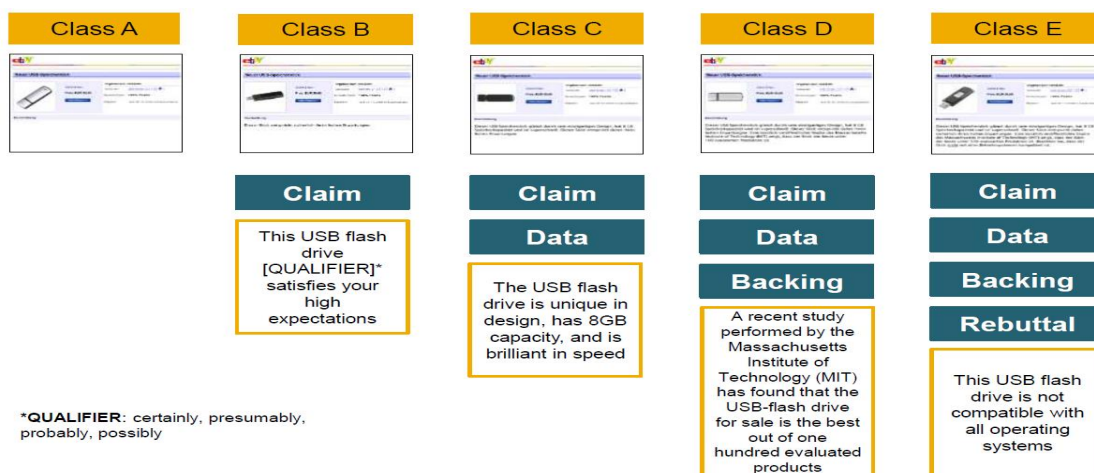

Figure 2. Trustworthiness Classes Based on Toulmin's (1958) Model of Argumentation (Adapted from Riedl et al., 2010b)

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[2] Note that we only used the given data set for our exemplified analysis.

2.2.3   Experimental Setup

In Riedl et al. (2010b), participants in the fMRI scanner had to press one of two corresponding buttons on a response box to indicate whether they considered an offer as trustworthy or untrustworthy. After the maximum time of 12 seconds, participants saw a fixation cross for three seconds before the next offer appeared, and the displays continued in this way (Mduration_of_stimulus = 3.61 seconds, SD = 1.63, range = [.78, 7.15]). The authors pseudo-randomized the sequence of offers for every subject. In total, every subject saw and evaluated 120 offers (4 × 30 eBay offers). The authors recorded the responses with specific software (COGENT; binary response with 1 = "trustworthy" and 0 = "untrustworthy"), and we calculated the mean evaluation (individual trustworthiness share, indTS) of all five trustworthiness classes (A, B, C, D, E) for each participant. They repeated each stimulus (i.e., A1 as stimulus 1 out of class A) four times so that we generated an individual trustworthiness share out of the sum of positive answers for the specific stimulus (i.e., A1) divided by four (hence, values ranged from 0 to 1). High values indicated that participants perceived the eBay offer in the respective class as trustworthy; low values indicated that the participants perceived the eBay offers as untrustworthy.

With regard to differences in trustworthiness ratings between the selected trustworthiness classes (Figure 3), we entered indTS into a one-way ANOVA (using trustworthiness classes A, B, C, D, E), corrected for repeated measures using the Greenhouse-Geisser (GG) correction criterion. Results indicated a significant main effect for trustworthiness class ($F_{(2.67, 50.46)}$ =22.11, p < .001) with significant increases from class A to class D (except for A to B) and a significant decrease from class D to class E (Figure 3). This result is in line with our assumptions that we derived based on Toulmin (1958) theory of argumentation.
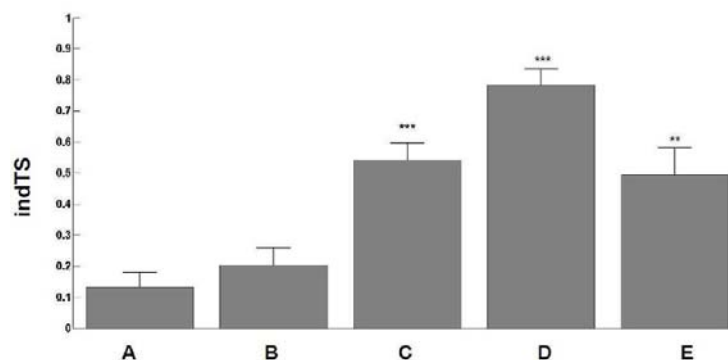

Figure 3. Mean and SEM for each Trustworthiness Class Based on indTS (p <.05; ***p < .001)**

2.2.4   Data Acquisition and Preprocessing

Riedl et al. (2010b) executed their study on a 3T fMRI scanner (Magnetom Trio, SIEMENS, Erlangen, Germany). The data set comprised 36 transversal slices of 3.6 mm thickness without a gap, a field of view of 230 mm x 230 mm, and an acquired matrix with 64 x 64 (i.e., isotropic voxels with 3.6 mm edge length). Contrast parameters were a signal response time of 3000 ms, an echo time of 50 ms, and a flip angle of 90°. The authors projected the pretest eBay offers, selected to be equal in size, position, background, and luminance in order to prevent external confounding visual stimulation, on a transparent screen with a LCD beamer.

We analyzed the data with the SPM8 freeware (Friston, 1996; Friston et al., 1995) and gPPI toolbox (McLaren et al., 2012), using MatLab as a working base. The data preprocessing included three initial steps. First, we used a "rigid body" transformation to the first image of the session (realignment) to realign all images. Second, to compare all participants in the group analysis, we normalized and re-sampled all images to the standard Montreal Neurological Institute (MNI) template (normalization). Third, to prepare the data for the statistical analysis, we smoothed all images with an 8mm Gaussian kernel (smoothing) (Ashburner, Neelin, Collins, Evans, & Friston, 1997).

2.3   fMRI Data Analysis: PPI Analyses

With regard to the concept of functional integration (see Figure 1), the applied PPI analysis serves as an example for analyzing the effects between different brain regions (Banks et al., 2007; Friston et al., 1997;

Gitelman et al., 2003; McLaren et al., 2012; O'Reilly et al., 2012; White & Alkire, 2003; Williams et al., 2006). A PPI analysis analyzes connectivity (McLaren et al., 2012) for chosen regions of interest (Gitelman et al., 2003) to investigate a connectivity of already observed regions (i.e., from the general group analysis see below). A PPI analysis also explores unobserved but behaviorally relevant interactions that are associated with processing and evaluating trustworthiness. To find these unobserved interactions, we use a generalized psychophysiological interaction (gPPI) approach due to its advantages in estimation and in modeling context-dependent connectivity (see McLaren et al., 2012).

2.3.1 Procedure

The first step is to conduct a general group analysis—a standard fMRI analysis—to extract relevant task-dependent regions of activation (see Appendix B for a whole description of the general group analysis). In the second step, one chooses relevant regions of interest based on either a priori expectations and previous research or on exploratory reasons. In the present example, we chose the ventral and dorsal anterior cingulate cortex (BA24/BA32) and the dorsolateral prefrontal cortex (dlPFC/BA9) as the regions of interest for the PPI analysis (see Appendix B, Figure B1b-d). We selected these brain regions based on our extensive literature review (see Appendix A, Table A1) that revealed the importance of regions in the anterior cingulate gyrus and prefrontal cortex in trust situations[3]. The anterior cingulate cortex is also essential in trust situations (see Appendix A, Table A1; Riedl & Javor, 2012). Though the ventral and dorsal areas of the anterior cingulate cortex have different roles (Bush, Luu, & Posner, 2000; Devinsky, Morell, & Vogt, 1995), in general, they are associated with conflict monitoring (Botvinick, Cohen, & Carter, 2004) and with the integration of reward and emotions in decision making processes (Botvinick, 2007; Botvinick, Cohen, & Carter, 2004; Deppe et al., 2007; Riedl & Javor, 2012). In addition to activation in trust situations, researchers have also found that the dlPFC plays a major role in coupling the information of rewards with actions (Heekeren et al., 2006; Lee & Seo, 2007) and for valuation and self-control (Hare et al., 2010). The next steps (steps three to six) involve conducting a PPI analysis. In step three, for each participant, we extracted a spherical mask of a chosen region-of-interest (ROI: a seed region) (McLaren et al., 2012) surrounding its activation peak (x, y, z coordinates (see Table 1)). In steps four to six, we applied the general linear model (GLM) of the standard fMRI analysis to our data (see Appendix B). At first, we estimated an additional PPI-specific GLM for each participant. In this specific GLM, we included three regressors of the basic GLM (R1-R3; and movement regressors) and two new PPI-specific regressors (R4 and R5): in more detail, (R1) was the regressor for all trustworthiness classes (A, B, C, D, E); (R2) was the regressor for aggregated trustworthiness share (aTS); (R3) was a regressor specifying all trials convolved with the canonical HRF; (R4) was the regressor for the interaction between neural activity in the given region-of-interest (seed region) and aTS, convolved with the canonical HRF; and (R5) was the BOLD mean from the selected seed region (see also Gitelman et al. 2003; McLaren et al., 2012). We removed variance associated with the six motion regressors from the extracted time series (Gitelman et al., 2003). We deconvolved[4] the time courses based on the model for the canonical hemodynamic response in order to construct a time series of neural activity in the region of interest. Using the PPI-specific GLM, we calculated single-subject contrasts to determine both positive and negative connectivity differences between the seed region and other brain regions for aTS. Based on this approach, we could identify connectivity between a seed region and other regions on an individual level. On the group level (second level), we computed a one-sample t-test over all subjects and generated statistical parametric maps for the given interaction contrast (positive, negative) that displayed the t-value of each peak voxel that met a $p < .005$ (uncorrected) significance level with an extent threshold voxel of $k = 10$ (for a similar procedure, see Hare et al., 2010). In step seven, for an independent beta-value extraction (for procedures, see, e.g., Litt, Plassmann, Shiv, & Rangel, 2011; Poldrack, 2006) as basis for effect visualization and separate extraction with regard to the five trustworthiness classes (A, B, C, D, E), we computed an additional GLM that separated regressors (R1-R5) and first-level single-subject contrasts of interest for each trustworthiness class (A, B, C, D, E). By using the spherical mask (ROI), we extracted for each participant an average of beta values within the ROI with regard to the modeled trustworthiness classes (A, B, C, D, E). See Figure 4 for a graphical overview of the whole procedure.

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[3] Additionally, studies using PPI analysis have previously investigated all three areas (Dosenbach et al., 2007; Hare et al., 2010; Hare, Malmaud, & Rangel, 2011; Schulz, Bédard, Czarnecki, & Fan, 2011).

[4] "The deconvolution simply estimates the best neuronal time course that, when convolved with the hemodynamic response function, reproduces the observed data" (Gitelman et al., 2003, p. 205).

	Step	Content	How	References
Standard fMRI-Analysis	**Step 1:** *General Linear Model (GLM)* **Step 2:** *Extracting significant regions*	• **Standard GLM Analysis for each participant** with: • Aggregated trustworthiness shares (aTS) for [A, B, C, D, E] as parametric modulation • **First-Level Contrasts:** • T-contrasts with increasing and decreasing aTS (aTS+; ATS-) • Extracting significant regions **on a group level**	• Standard procedure for fMRI-analysis using event-related or block design	See for example, Dimoka (2012); Huettel et al., (2009)
ROI-selection	**Step 3:** *Selection of region-of-interest (ROI)*	• Seed region from the **single subject** contrast dlPFC	• Selection of region based on a-priori results or exploration • Back-Up with existing literature and research	See for example, Poldrack (2007)
PPI-analysis	**Step 4:** *Extraction of BOLD signal time-series* **Step 5:** *Interaction term* **Step 6:** *GLM with PPI-Components*	**PPI – Analysis: Main Steps** dlPFC — ? — ? aTS+; aTS- • Extraction of the BOLD time-series adjusted for the main effect of trustworthiness shares, • Here: DLPFC within a 8mm sphere around the activation peaks for each participant • Interaction term between the source region (DLPFC) and the experimental parametric conditions ([aTS+] and [aTS-]). • Deconvolving of the extracted time course based on the model of the canonical hemodynamic response • regressors of the *standard GLM* and **new PPI-specific regressors:** o *(R1) a regressor for all trustworthiness classes (A, B, C, D, E)* o *(R2) a regressor for aTS* o *(R3) **a regressor specifying all trials convolved with the canonical HRF*** o *(R4) **a regressor for the interaction between neural activity in the given region-of-interest (seed region) and aggregated trustworthiness share (aTS), convolved with the canonical HRF*** o *(R5) **the BOLD mean from the selected seed region.**.* dlPFC vmPFC aTS+; aTS-	• either Graphical User Interface (GUI)-based or script based • BOLD time-series extraction Single step for each participant using a given software package (i.e. SPM12 → PPI button within the GUI) • all in one routine using a batch interface (i.e. for SPM12) or • script based approach using gPPI	See for example, McLaren et al. (2012); Reilly et al. (2012); See for a detailed step by step instruction for a given software: for example spm12; http://www.fil.ion.ucl.ac.uk/spm/
	Step 7: *Plotting results*	• Extraction of beta values from the seed region, DLPFC and interacting region VMPFC • 8mm sphere around the activation peaks for each participant and trustworthiness classes [A, B, C, D, E]		

Figure 4. Overview of Steps for Applying a PPI Analysis

2.3.2   Results

For the first and second seed region—ventral (vACC) and dorsal anterior cingulate gyrus (dACC)—we found a positive task-related functional connectivity (regarding aTS) within the right inferior frontal gyrus (BA9) for both the vACC (peak: x = 60, y = 10, z = 34; T = 4.60; k = 76 voxel) and the dACC (peak: x=56, y = 10, z = 38; T = 3.20; k = 16 voxel) (see Appendix, Table C1). A conjunction—a simultaneous overlay of selected contrasts from the PPI—with 1) vACC and 2) dACC as seed regions and 3) from the general group analysis showed: 1) an overlap between the two mentioned clusters of the PPI analysis (with vACC and dACC) within the right inferior frontal gyrus (BA9) and 2) an overlap in both regions with the previously observed cluster within the inferior frontal gyrus (dlPFC/BA9; x = 52, y = 14, z = 40; T = 5.25; k = 211 voxel; see Appendix B, Table B1) from the general group analysis (see Figure 5a). Bivariate correlation analysis of extracted and aggregated beta estimates (for each subject and trustworthiness class (GLM2)) revealed general significant correlations between each seed region and the observed cluster within the dlPFC (right vACC (rvACC) =.529, p < .001; right dACC (rdACC) = .678, p < .001) (see Figure 5b-c). We gained more detail from observations with respect to the trustworthiness class—that vACC – dlPFC interactions were strongest for class A (rvACC = .639, p = .002) and class E (rvACC = .610, p = .004), whereas dACC – dlPFC interactions were stronger for class B (rdACC = .764, p < .001) and class C (rdACC = .748, p < .001).
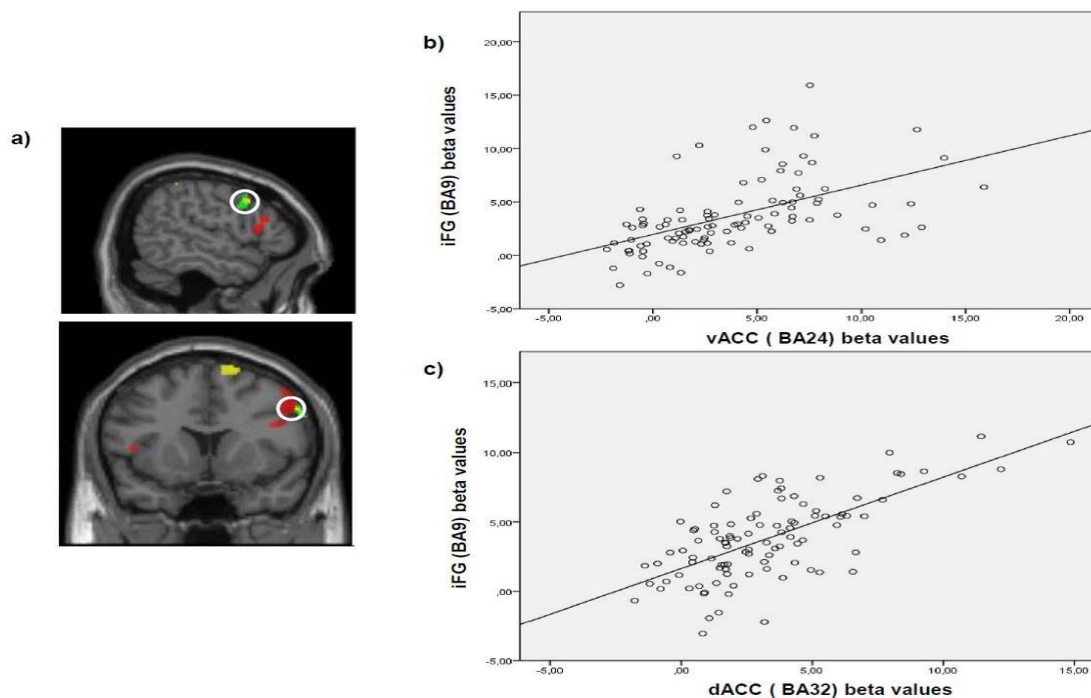
Figure 5. A) Overlap (Green Spot) Within Right Inferior Frontal Gyrus (dlPFC/BA 9); Results of PPI and Correlation of Beta Values etween B) vACC and dlPFC and C) dACC and dlPFC

As for the third seed region, the dorsolateral prefrontal cortex (dlPFC/BA9), we found (see Table B1) a negative task-related functional connectivity within the left medial frontal gyrus (vmPFC/BA10; peak: x = -2, y = 44, z = -8; T = 3.72; k = 10 voxel) (see Figure 6a). Importantly, compared to the results of the general group analysis and the PPI analysis of the vACC and dACC, this connectivity is an identified interaction between the dlPFC and a region (the vmPFC) that we did not find in the general group analysis (see Table B1). Thus, the PPI analysis revealed a new region that is important for decision making in trust contexts. Bivariate correlation analysis of extracted and aggregated beta estimates for each subject and trustworthiness class (GLM2) showed general significant correlations between the seed region (dLPFC) and the observed cluster within the ventromedial prefrontal cortex (r = -.382, p < .001) (see Figure 6b). More specifically, the dlPFC-vmPFC connectivity was significantly stronger, especially for trustworthiness classes B (rdlPFC=-.429, p=.059), C (rdlPFC = -.417, p = .067) and E (rdlPFC = -.477, p = .033), but not for trustworthiness classes A (rdlPFC = .232, p = .324) and D (rdlPFC = -370, p = .109).

Taking this identified connectivity and exploring the relevance of dlPFC and vmPFC interaction for decision making processes and for valuation (Bartra, McGuire, & Kable, 2013; Hare, Camerer, & Rangel,

2009; Hare et al., 2010; 2011), we used a moderated regression analysis (Hayes, 2012) with values of the individual trustworthiness share for each class (indTS) as the dependent variable, and with the extracted and averaged parameter estimates (for each subject and trustworthiness class (GLM2) of the dlPFC, the vmPFC, and the interaction term of both (betavmPFC x betadlPFC) as independent variables. We found no significant main effect for the dlPFC and vmPFC, but we did see a significant negative interaction effect of dlPFC and vMPFC signals on the trustworthiness share (see Table 1 for results and Figure 6c for the interaction effect).

Table 1. Results for Moderated Regression Analysis

Construct	DV Individual trustworthiness share/class				
	Coefficients	T	p	LLCI	ULCI
Beta$_{vmPFC}$	.0257	1.6479	.1026	-.0053	.0567
Beta$_{dlPFC}$	.0013	0.1063	.9156	-.0235	.0262
Beta$_{vmPFC}$ * Beta$_{dlPFC}$	-.017	-3.0876	.0026	-.0280	-.0061
R^2 = .0942; $F(3, 96)$ = 3.3279, p = .0228 Note: LLCI = lower-level confidence interval; ULCI = upper-level confidence interval.					
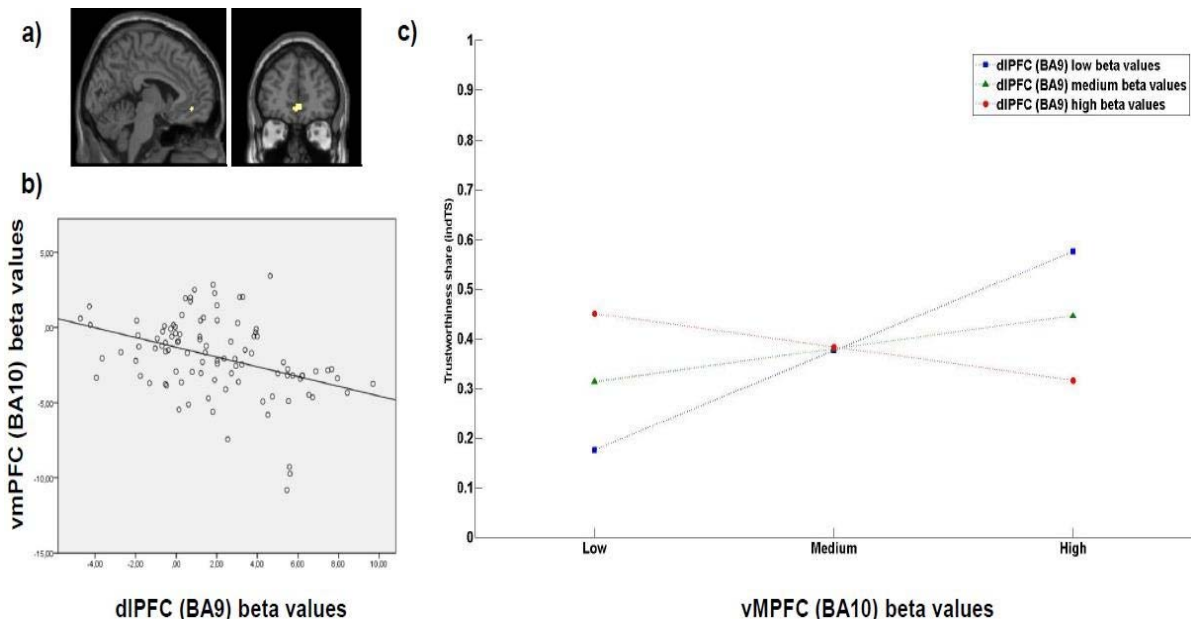
Figure 6. A) vmPFC, B) Results of PPI and Correlation of Beta Values Between dlPFC (Seed Region) and vmPFC, and C) Interaction Effect of dlPFC and vmPFC With Respect to Averaged Trustworthiness Share (aTS)

3   Discussion and Implications for Future Research

For IS research, one needs to understand how people make decisions in IS-relevant contexts to optimize the interaction between humans and information and communication technologies. Thus, if one accepts that better understanding the human brain means better understanding human decision making, the integration of neuroscientific methods and findings into IS research has the potential to yield important findings (Dimoka, Pavlou, & Davis, 2007; Dimoka et al., 2011, 2012; Riedl, 2009; Riedl et al., 2010a; 2014a; von Brocke & Liang, 2014). We introduce psycho-physiological interaction analysis (PPI) to neuroIS as a methodological extension that enables another form of analyzing fMRI data. In accordance with the concept of functional integration (Friston, 1994), we exemplarily focus on the fact that the emergence of complex mental processes such as trust in IS contexts is based on activity in a network of brain regions rather than on activity in one area alone (Friston, 2002; Friston et al., 2011; Hare et al., 2010; Heim et al., 2009). Thus, with regard to functional integration, applying a PPI analysis of brain

imaging data (Friston et al., 2011; Stephan et al., 2008, 2010) could lead to a deeper understanding of the nature and dimensionality of IS constructs (Dimoka et al., 2011). That said, our paper's main contribution is to show the methodological potential that PPI offers for IS research. Moreover, reaching beyond the methodological contribution of this paper, we also provide further insight into IS research (e.g., trust research) and implications that may motivate future research by identifying three main applications where connectivity analysis can enrich IS research (see Figure 7).
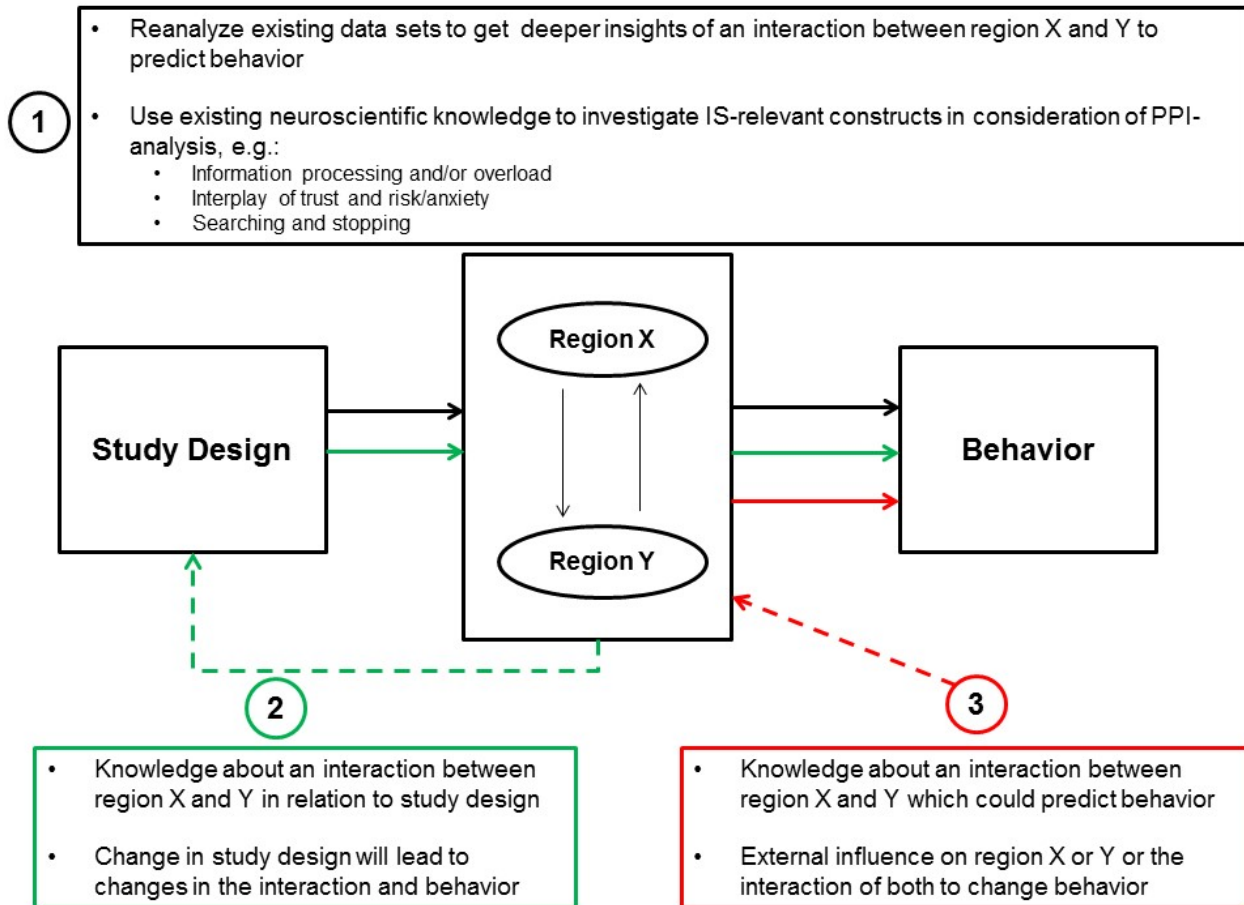

Figure 7. Overview of How PPI Analysis Can Enrich NeuroIS Research

For the first application (**reanalyze and use existing neuroscientific knowledge**), there is the potential to reanalyze existing data sets (e.g., Dimoka, 2010; Kopton et al., 2013; Riedl et al., 2014b; Warkentin et al., 2016) and further analyzing work-in-progress data. Here, connectivity analysis can help one to obtain deeper insights into interactions between different observed and unobserved regions that might be important to predict behavior.

With regard to our exemplary data reanalysis for which we used a published data set (Riedl et al., 2010), we started with an analysis based on parametrical contrasts (see Appendix B). We found activation in parts of the dorsal striatum when shares of trustworthiness increased and activation in the vACC, dACC, and dLPFC when shares of trustworthiness decreased (see Table B2). These results of the general group analysis are in line with neuroscientific findings reported in fMRI trust research in cognitive neuroscience, neuroeconomics, and neuroIS (see Table A1 for an overview). Based on these neural correlates and the concept of functional integration (Friston, 1994), we conducted a PPI analysis to make a first step of considering the complexity of brain processes in neuroIS research. With regard to the exemplarily chosen brain regions of vACC, dACC, and dlPFC, PPI analysis revealed a positive task-dependent connection of BOLD activation of the vACC and dACC (as seed regions) and in the dlPFC with decreased shares of trustworthiness (see Figure 5). We gained more detailed information from observations with respect to the trustworthiness class; namely, that vACC–dlPFC correlations were strongest for class A and class E, whereas dACC–dlPFC correlations were stronger for class B and class C. In line with research that shows

various functions of parts of the ACC (Botvinick et al., 2004; Bush et al., 2000; Bush et al., 2002; Kennerley, Walton, Behrens, Buckley, & Rushworth, 2006; Riedl & Javor, 2012), this result suggests that, in the present context of trust information processing, the influence of vACC and dACC activation on dlPFC activation is a function of the importance of the level of trustworthiness and trustworthy arguments. In essence, the interplay between the vACC and the dlPFC might be more relevant for the evaluation of classes with very low trustworthiness and devaluation and may be in line with assumptions regarding emotion integration and conflict regulation in decision making (Bush et al., 2000; Etkin, Egner, & Kalisch, 2011).

In contrast, the connection between the dACC and the dlPFC seems to be more important for classes with ambiguous information (i.e., medium levels of trustworthiness), which may be attributed to the role of the dACC in conflict monitoring, evaluation, and cognitive control (Botvinick et al., 2004; Delgado et al. 2005, Dosenbach et al., 2007; Etkin et al., 2011; Kerns et al., 2004; Sanfey, Rilling, Aronson, Nystrom, & Cohen, 2003; Schulz et al., 2011; Seeley et al., 2007; Weber, Rangel, Wibral, and Falk, 2009). Considering Dimoka et al.'s (2011) paper on the potential of cognitive neuroscience for IS research, our results indicate that brain activity does not correspond linearly to behavior (here, trustworthiness ratings). Rather, specific brain areas are more closely related to information processing in situations in which the meaning of a stimulus is relatively clear (here, situations with very low or very high trustworthiness), while other areas come into play when the meaning of a stimulus is ambiguous and one seeks to mitigate the ambiguity and transform the situation into one with more clarity. (Plassmann, Kenning, Deppe, Kugel, & Schwindt, 2008). Against this background, the results of the PPI analysis show that, particularly with regard to more ambiguous or devalued stimulus classes (especially B, C, and E), the influence and relevance of structures in the anterior cingulate cortex (here, vACC and dACC) and the dlPFC, seem to be more important with regard to decision making processes compared to distinctively low (class A) or high (class D) trustworthiness classes. These results indicate that it might be interesting to investigate trust relevant processes not only related to their neural correlates but also to their interdependencies based on existing knowledge (see Table A1).

This interdependency also leads to **using existing neuroscientific knowledge** for IS-relevant contexts in order to develop new research ideas that consider the possibilities of PPI analyses. First, the complex nature of many IS constructs calls for exploratory research to 1) identify relevant neural correlates and 2) discuss these results in relation to existing neuroscientific knowledge. Second, one has more possibilities to conduct confirmatory research if one studies IS constructs that have already been examined in neuroscientific research in general and in neuroIS studies in particular. Indeed, in our exemplary study, we considered research on trust processes (see Table A1) in which we began by investigating neural correlates and localizations to validate existing neuroscientific results and to broaden the understanding of the complex nature of an IS relevant context (see Table B1). We then used the given knowledge and data (see Table A1) and investigated temporal interdependencies between observed (i.e., vACC, dlPFC) and unobserved regions (vmPFC) for a possible prediction of behavior. Following this procedure and with the extensive neuroscientific studies about trust (see Table A1) and risk processes (e.g., Mohr, Biele, & Heekeren, 2010) could involve developing new research questions that consider the possibilities of PPI analysis. For example, it might be interesting not only to investigate different trust and risk levels in an IS setting (Pavlou & Gefen, 2004) but also to take a look at the importance and strength of these processes for decision making by investigating neural connectivity between relevant regions for trust, risk, and both constructs. As another example, one could investigate searching and stopping behavior (Browne & Pitts, 2004; Browne, Pitts, & Wetherbe, 2007). If we consider neuroscientific literature about information processing (Dux, Ivanoff, Asplund, & Marois, 2006; Marois & Ivanoff, 2005), as well as inhibition processes (Li, Huang, Constable, & Sinha, 2006; Simmonds, Pekar, & Mostofsky, 2008; Swick, Ashley, & Turken, 2011), a first step could be again to localize brain structures relevant for searching and stopping in an IS context. This step is important to validate existing results and to consider possible differences between neuroscientific study settings and IS contexts. In a next step, one could identify prior observed or unobserved regions with PPI or related methods that might influence regions responsible for stopping information search behavior. One can apply a similar procedure to investigate other important IS constructs, including technology anxiety (i.e., Chua, Chen, & Wong, 1999; Yang & Forney, 2013), visual perception (i.e., Bauerly & Liu, 2008; Everard & Galletta, 2005; Reinecke et al., 2013), and information overload (Jones, Ravid, & Rafaeli, 2004).

Altogether, we can conclude that neuroIS research should consider the rapid methodological advancements in brain research and the functioning of the human brain (Friston et al., 2011). With regard to the exemplary study, from the general group analysis and following the concept of functional

specialization (Friston, 1994), we know which regions might be involved in processing increasing and decreasing averaged trustworthiness shares (aTS). Yet, we do not know how the extracted regions are directly or indirectly linked to behavior and decision making or how they interact with each other. Moreover, we do not know whether brain regions that we did not observe in these first two steps of data analysis might be indirectly important for the trustworthiness evaluation. Therefore, applying PPI might be important, particularly to develop a better understanding of the nature and dimensionality of trust processes and IS relevant constructs in general (Dimoka et al., 2011). Nevertheless, IS related concepts are typically more complex than frequently studied constructs in neuroscience, and, therefore, the localization and the notion of localized brain functions remains important and should be supported (see, for example, Camerer & Kenning, 2013). The notion of localized brain functions is particularly important when investigating IS constructs based on neuroscientific methods, which have not been investigated before. Based on the results of functional specialization (Friston et al., 2011), further methods in relation to brain connectivity and functional integration could then be fruitful to deepen and broaden existing knowledge and theories.

With regard to the second application (**study design**), a contribution for neuroIS research using PPI or other techniques investigating brain connectivity (i.e., DCM) (Stephan et al., 2008, 2010) emerges from knowledge about temporal and causal relations between different brain regions: because of this knowledge, experimental setup adjustments (i.e., changes in stimuli design, different samples, and different manipulation) could lead to changes in the interaction between region X and Y and, therefore, influence behavior. With regard to our example of trust processing, we know, with the dlPFC as seed region, that we observed a negative task-dependent interaction of BOLD activation in the dlPFC and the ventromedial prefrontal cortex (vmPFC; as an unobserved region) for decreasing shares of trustworthiness evaluations (see Figure 6). More specifically, the dlPFC–vmPFC interaction was significantly stronger, especially for stimulus classes B, C and E, but not for stimulus classes A and D. This result shows that, for each class, there might be a mediating influence on trustworthiness perception between the dlPFC and the vmPFC, with stronger negative relations for classes B, C, and E. Furthermore, the vmPFC, as an important region for decision making and information processing (Hare et al., 2009, 2010; Kahnt, Heinzle, Park, & Haynes, 2011; Naqvi, Shiv, & Bechara, 2006), showed no significant BOLD activation in the general group analysis, which could indicate a less direct effect of vmPFC activation on trustworthiness processing but a more direct effect on decision making by integrating different information into the decision making process. Our behavioral analysis (moderated regression analysis; see Table 2 and Figure 6) confirms this interpretation: we observed no main effect but did see a significant interaction effect of dlPFC and vmPFC activation in predicting trustworthiness evaluations. This result is crucial and is in line with research in cognitive neuroscience (Hare et al., 2009, 2010). Thus, the main implication for neuroIS research is that, while prior fMRI studies based on the concept of functional specialization (Figure 1) have identified the vmPFC as crucial in trust situations (see Table A1 for corresponding studies), our analysis of effective connectivity revealed that the vmPFC alone seems not to be trust specific (at least not in our experimental task of processing and evaluating eBay offers). Rather, this brain region becomes behaviorally relevant in trust situations when functioning together with other brain regions (here, the dlPFC). Based on this knowledge, one could develop new research questions by 1) adjusting the experimental setup (i.e., other stimuli, different shops), 2) changing information (rational, emotional, utilitarian, hedonism), 3) changing the visual presentation, and 4) changing perception and salience, which, in consequence, could lead to alterations in the interaction between region X (here: DLPFC) and region Y (here: VMPFC),and might lead to a behavioral difference (here, trustworthiness evaluations).

With regard to the third application (**external factors**), another contribution for neuroIS research might stem from other "external" insights (independent from the current research questions) about a certain brain region. For example, with regard to our exemplary study, we know from our PPI analysis the temporal interaction between the DLPFC and VMPFC, which, in consequence, can predict behavioral changes. From neuroscientific findings, we also know that the DLPFC is highly relevant for tasks associated with cognitive effort and depletion (Hedgcock, Vohs, & Rao, 2012; Nee, Wager, & Jonides, 2007; Swick et al., 2011). It would be interesting to integrate these independent findings in the experimental setup. For example, one could use a cognitive task (i.e., stroop task, flanker task, go/no-go task (Nee et al., 2007; Swick et al., 2011)) before one's experimental setup to change activity in the DLPFC. It would then be interesting to know if the stimulation of the DLPFC by such an "external" cognitive task also influences the temporal interaction with the VMPFC in our experimental setup and, thus, changes trustworthiness evaluations.

Altogether, based on advanced methods for analysis of fMRI data, the present procedure and exemplified study confirms that one can identify novel insights of brain-behavior interaction in IS contexts by using PPI analysis. These applications help to reveal the causal mechanism that underlie the formation of perceptions, preferences, beliefs, attitudes, behavioral intentions, and actual behavior in IS contexts. With our study, we hope to further advance the promising field of neuroIS and stimulate new methodological discussions and further IS-relevant research.

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Appendix A: Overview of fMRI Studies and Corresponding Neural Correlates of Trust

Table A1. Overview of fMRI Studies and Corresponding Neural Correlates of Trust

Paper	Sample size (female/male) / experimental paradigm (stimulus)	Basic research question and/or context	Main Findings
Aimone, Houser, & Weber (2014)	60 (30/30) / trust game	A rapidly expanding literature reveals economically important differences between risky and trusting decisions and further suggests that these differences are due to "betrayal aversion". While its neural foundations have not been previously illuminated, the prevailing hypothesis is that betrayal aversion stems from a desire to avoid negative emotions that arise from learning one's trust was betrayed. Here, the authors provide evidence from an fMRI study that supports this hypothesis.	- For initial evidence on the neural correlates of betrayal aversion, the authors compared the average BOLD activity when playing with a human counterpart, against playing with a computer mediator. The results revealed activity in the **right anterior insular cortex** and in the **medial frontal cortex** and **right dorsolateral prefrontal cortex**. - The opposite contrast did not show any significant activation. - When agents make the decision to trust in contrast to the safe option to not trust, the authors observed increased activity in the **right anterior insular cortex** and the **mid-anterior cingulate**. - The interaction between the chosen option and the identity of the counterpart again revealed significantly higher activity in the **right anterior** and **posterior insular cortex** when the subject decided to trust and the counterpart was a human player in contrast to a computer player, which provides further evidence that the **insula** reflects the heightened negative state associated with betrayal aversion. - As the level of betrayal aversion increased, subjects showed greater **insular activity** when choosing the risky option while playing with a human counterpart compared to with a computer mediator.
Baumgartner et al. (2008)	49 (0/49) / trust game	What are the neural mechanisms of trusting behavior by intranasal, double-blind administration of oxytocin?	- Subjects in the oxytocin group showed no change in their trusting behavior after they learned that their trust had been breached several times while subjects receiving placebo decrease their trust. - This difference in trust adaptation was associated with a specific reduction in activation in the **amygdala, the midbrain regions,** and **the dorsal striatum** in subjects receiving oxytocin, suggesting that neural systems mediating fear processing (**amygdala** and **midbrain regions**) and behavioral adaptations to feedback information (**dorsal striatum**) modulate oxytocin's effect on trust.

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Bereczkei, Deak, Papp, Perlaki, & Orsi (2013)	27 (14/13) / trust game	Prediction of high-Machiavellian people showing elevated activity in the brain areas involved in reward seeking, anticipation of risky situations, and inference making.	▪ Consistent activation in high Machs' thalamus and **anterior cingulate cortex** (player 1) and in **dorsal anterior insula/inferior frontal gyrus** (player 2). ▪ The authors compared the group activation of high-Mach (HM) and low-Mach (LM) participants during the decision making process in the trust game contrasted to the control phase. Whole-brain two-sample t-tests revealed a significantly higher activation during game > control condition for the HM group in comparison with the LM group. ▪ The authors found a bilateral neural response in the **superior frontal and middle frontal gyrus**. They detected right hemispheric activation in the **anterior insula**, **inferior frontal gyrus**, **precuneus**, and **cerebellum**. ▪ In the left hemisphere, the **lingual gyrus** and the **globus pallidus** showed elevated activation. ▪ The contrast examining the brain activation as a first player (investor > control) yielded bilateral response in the **superior frontal**, **middle frontal gyrus**, **middle temporal gyrus,** and the **globus pallidus**. ▪ They found significant activation in the right middle occipital gyrus, fusiform gyrus, precuneus and anterior cingulate cortex, and the right thalamus and putamen. ▪ In the left hemisphere, they detected activation in the **lingual gyrus**, **cuneus** and the **superior occipital gyrus**. When the trustee role was contrasted to the baseline (trustee > control), the authors detected increased activation in the **left superior frontal** and **middle frontal gyrus**, in the **right anterior insula**, **inferior frontal gyrus** and **parahippocampal gyrus**.
Bos, Hermans, Ramsey, & van Honk (2012)	16 (16/0) / faces	In a placebo-controlled testosterone administration study with 16 young women, the authors sought to obtain more insights into neural mechanisms whereby testosterone acts on trust.	▪ Several cortical systems, including the **orbifrontal cortex** (OFC), are involved in the evaluation of facial trustworthiness. ▪ Testosterone administration decreased functional connectivity between **amygdala** and the **OFC** during judgments of unfamiliar faces and also increased **amygdala** responses specifically to the faces that were rated as untrustworthy. ▪ Finally, connectivity between the amygdala and the brain stem was not affected by testosterone administration.
Carter, Bowling, Reeck, & Huettel (2012)	18 (10/8) / poker game	Prediction of human participants' subsequent decisions in an incentive-compatible poker game.	▪ Signals from the **temporal-parietal junction** (TPJ) provided unique information about the nature of the upcoming decision, and that information was specific to decisions against agents who were both social and relevant for future behavior.
Chang, Smith, Dufwenberg, & Sanfey (2011)	30 (10/20) / trust game	Why do people often choose to cooperate when they can better serve their interests by acting selfishly? One potential mechanism is that the anticipation of guilt can motivate cooperative behavior. The authors used a formal model of this process in conjunction with fMRI to identify brain regions that mediate cooperative behavior while participants decided whether or not to honor a partner's trust.	▪ Observation of increased activation in the **insula**, **supplementary motor area**, **dorsolateral prefrontal cortex** (PFC), and **temporal parietal junction** when participants were behaving consistently with the proposed model and increased activity in the **ventromedial PFC**, **dorsomedial PFC**, and **nucleus accumbens** when they chose to abuse trust and maximize their financial reward.

Table A1. Overview of fMRI Studies and Corresponding Neural Correlates of Trust

Delgado et al. (2005)	12 (5/7) / trust game	Investigation of whether prior social and moral information about potential trading partners affects the striatal circuitry. Participants made risky choices about whether to trust hypothetical trading partners after having read vivid descriptions of life events indicating praiseworthy, neutral, or suspect moral character.	▪ Despite equivalent reinforcement rates for all partners, participants were persistently more likely to make risky choices with the "good" partner. ▪ As expected from previous studies, activation of the **caudate nucleus** differentiated between positive and negative feedback but only for the "neutral" partner. ▪ Notably, it did not do so for the "good" partner and did so only weakly for the "bad" partner, suggesting that prior social and moral perceptions can diminish reliance on feedback mechanisms in the neural circuitry of trial-and-error reward learning. ▪ In addition, the authors found that the **ventral portions of the striatum** also play an important role in trust situations because they are crucial for making predictions and anticipating the outcome of risky decisions. ▪ Finally, the study revealed high activation of the **insular cortex** and the **cingulate cortex** in trust situations—the former brain structure is important for the perception and processing of negative emotions (e.g., uncertainty), whereas the latter is important for the processing of cognitive conflict.
Dimoka (2010)	15 (6/9) / eBay websites	Given the importance of studying both trust and distrust, this study aims to shed light on the nature, dimensionality, distinction, and relationship, and relative effects of trust and distrust on economic outcomes in the context of impersonal IT-enabled exchanges between buyers and sellers in online marketplaces.	▪ First, results show that trust was associated with the brain's reward, prediction and uncertainty areas, while distrust was associated with the brain's intense emotions and fear-of-loss areas. ▪ While the corresponding psychometric data could not clearly distinguish between trust and distrust, the brain data suggest that trust and distrust and their dimensions are distinct and that they activate different brain areas. ▪ Second, the study separated the dimensions of trust and distrust by showing that credibility and discredibility were primarily associated with the brain's cognitive areas (**prefrontal cortex**), while benevolence and malevolence were mainly associated with the emotional areas (**limbic system**). ▪ Third, the identified brain areas adequately predicted price premiums and the levels of brain activation had a stronger predictive power than the corresponding self-reported psychometric measures.
Emonds, Declerck, Boone, Seurinck, & Achten (2014)	35 (22/13) / prisoner's dilemma	The biological roots for the proselfs/prosocials concept are explored by investigating the neural correlates of cooperative versus defect decisions when participants engage in a series of one-shot, anonymous prisoner's dilemma situations.	▪ When confronted with a PD situation, prosocials who also were high-trusting cooperated significantly more compared to prosocials who were low in dispositional trust. ▪ For proselfs, the effect of trust, if any, was in the other direction, with high-trusting proselfs cooperating less than those who were low in trust. ▪ Results from the fMRI data: Hypothesized areas where prosocials showed more activation compared to proselfs were **right TPJ** (BA 40), **right medial frontal cortex** (BA 8), and **left and right precuneus** (BA 7). ▪ The **anterior superior temporal gyrus** (STG, BA 22), which was hypothesized to show more activation in the prosocial group, did not survive cluster-size thresholding. However, slightly lowering the threshold yielded an additional significant cluster in the STG (BA 22). ▪ Brain regions that were significantly affected by the interactive effect of trust and social value orientation showed that three of the five significant clusters lie in regions associated with social cognition: the **STG** within the **TPJ** (BA 39), the **medial frontal gyrus** (BA 9), and the **precuneus** (BA 31). ▪ Apparently, activation in these regions seemed to increase with higher dispositional trust scores, but, contrary to the hypothesis, the marginal effect of trust was greater for the proself group. ▪ Prosocials who decided to cooperate (rather than defect) showed a larger difference in **precuneus activation** compared to proselfs.

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Fareri, Chang, & Delgado (2012)	18 (9/9) / trust game	• Increased **striatal** and **anterior cingulate** BOLD activity for positive versus negative trust game outcomes emerged, which further correlated with model-derived prediction error learning signals. • These results suggest that consistent information through reward-learning mechanisms can continually shape initial impressions formed from direct social experience.
	Do initial impressions formed through experience modulate the ability to update social impressions at the behavioral and neural level? Investigation of the role of experienced social information on trust behavior and reward-related BOLD activity.	
Fett, Gromann, Giampietro, Shergill, & Krabbendam (2012)	45 (0/45) / trust game	• Imaging data showed correlations between age and BOLD signal during investments by condition: • In the cooperative condition, age was positively associated with increasing brain activation in foci in the left **TPJ**, extending into the **inferior parietal lobule**. There was also activation evident in the **bilateral middle frontal gyri** and **right precentral gyri**. • A negative correlation between brain activation and age was present in the **orbitofrontal cortex**, the **left and right caudate nucleus** and the **bilateral dorsomedial prefrontal cortex**. • In the unfair condition, increasing age was correlated with increasing activation in the **left TPJ** including the **inferior parietal lobule** and the **mid-cingulate gyrus**. • Increasing age was also associated with decreasing signal in the left **posterior cingulate gyrus**, **thalamus** and the **bilateral dorsomedial prefrontal cortex**. • An interaction between age and condition was present in the **posterior cingulate gyrus** and **precuneus** and within foci in the **lingual gyrus**. • With increasing age, these structures were more sensitive to cooperation. • An opposite activation pattern was present for the **anterior cingulate gyrus** (i.e., with increasing age the anterior cingulate became more active in response to unfair behavior).
	The tendency to trust and to cooperate increases from adolescence to adulthood. This social development has been associated with improved mentalizing and age-related changes in brain function. Thus far, there is limited imaging data investigating these associations. The authors used two trust games with a trustworthy and an unfair partner to explore the brain mechanisms underlying trust and cooperation in subjects ranging from adolescence to mid-adulthood.	
Fouragnan et al. (2013)	18 (0/18) / trust game	• The results were consistent with previous studies in showing that **striatal activation** patterns correlate with behaviorally estimated reinforcement learning measures. • However, the study additionally showed that this correlation was disrupted when reputational priors on counterparts were provided. • Indeed, participants continued to rely on priors even when experience shed doubt on their accuracy. • Notably, violations of trust from a cooperative counterpart elicited stronger **caudate** deactivations when priors were available than when they were not. • However, tolerance to such violations appeared to be mediated by prior-enhanced connectivity between the **caudate nucleus** and **ventrolateral prefrontal cortex**, which anti-correlated with retaliation rates. • Moreover, on top of affecting learning mechanisms, priors also clearly oriented initial decisions to trust, reflected in **medial prefrontal cortex** activity.
	Humans learn to trust each other by evaluating the outcomes of repeated interpersonal interactions. However, available prior information on the reputation of traders may alter the way outcomes affect learning. Investigation of the direct comparison of interaction-based and prior-based learning.	
Kang, Williams, Clark, Gray, & Bargh (2011)	16 (n.a.) / trust game	• The **left-anterior insular region** activated more strongly than baseline only when the trust decision was preceded by touching a cold pack and not a warm pack. • In addition, greater activation within **bilateral insula** was identified during the decision phase followed by a cold manipulation (contrasted to warm). • These results suggest that the **insula** may be a key shared neural substrate that mediates the influence of temperature on trust processes.
	Investigation of physical temperature as one factor that can influence human trust behavior and of the insula as a possible neural substrate.	

Table A1. Overview of fMRI Studies and Corresponding Neural Correlates of Trust

King-Casas et al. (2005)	96 (n.a.) / trust game	Investigation of neural substrates of social interactions by scanning the brains of multiple subjects engaged in a social interaction.	▪ Results suggest that reciprocity expressed by one player strongly predicts future trust expressed by their partner—a behavioral finding mirrored by neural responses in the **dorsal striatum**. ▪ Here, analyses win and between brains revealed two signals – one encoded by response magnitude and the other by response timing. ▪ Response magnitude correlated with the "intention to trust" on the next play of the game, and the peak of these "intention to trust" responses shifted its time of occurrence by 14 seconds as player reputations developed. ▪ This temporal transfer resembles a similar shift of reward prediction errors common to reinforcement learning models, but in the context of a social exchange. ▪ These data extend previous model-based functional magnetic resonance imaging studies into the social domain and broaden our view of the spectrum of functions implemented by the **dorsal striatum**.
Kopton et al. (2013)	20 (9/11) / Facebook user profiles	Exploring the initial trust building cognitive and affective processes in social networking sites with the help of fMRI in order to better understand trust development underlying users' initial connecting behavior in social networks.	1. For a higher trustworthiness condition (picture): ▪ For the contrast analysis "user profiles with pictures" > "user profiles without pictures", there was a significantly stronger activation for the **fusiform area** (temporal occipital fusiform cortex). ▪ For the condition "user profile with picture", there was a stronger brain activation in the 1) **frontal pole (BA 10)**, which is known to play a crucial role in complex cognitive processing; 2) the **precuneus and the cingulate gyrus (BA 31)**, which both represent the transition between the rather affective- and rather cognitive processing areas; and 3) the **lateral occipital cortex (BA 19)**, which is the main area for processing visual stimuli. ▪ Furthermore, the authors observed stronger activation in the **amygdala**, which is a part of the limbic system and mainly responsible for the neural implementation of emotions, including trust decisions. 2. For a lower trustworthiness condition (no picture): ▪ For the condition "user profile without picture", there was only stronger activation for the **intracalcarine cortex (BA 18)**, a region mainly known for visual processing. 3. For different textual information conditions: ▪ The "user profiles with positive textual information" were mainly processed by **right-lateral brain structures**, whereas the "user profiles with negative textual information" were mainly processed by **left-lateral brain structures**. ▪ Additionally, different areas for processing of visual stimuli were activated by profiles with and without textual information.
Krueger et al. (2007)	44 (22/22) / trust game	Investigation of the underlying brain mechanisms of conditional and unconditional trust in social reciprocal exchange.	▪ Results show that the **paracingulate cortex** was critically involved in building a trust relationship by inferring another person's intentions to predict subsequent behavior. ▪ This more recently evolved brain region can be differently engaged to interact with more primitive neural systems in maintaining conditional and unconditional trust in a partnership. ▪ Conditional trust selectively activated the **ventral tegmental area**, a region linked to the evaluation of expected and realized reward, whereas unconditional trust selectively activated the **septal area**, a region linked to social attachment behavior. ▪ The interplay of these neural systems supports reciprocal exchange that operates beyond the immediate spheres of kinship, one of the distinguishing features of the human species.
Lauharata-nahirun, Christopoulos, & King-Casas (2012)	30 (n.a.) / trust Game	Investigation of risk-related hemodynamic activity and individual preferences for two sets of options that differ only in the social or non-social nature of the risk. Risk preferences in social and non-social contexts were systematically related to neural activity during decision and outcome phases of each choice.	▪ Individuals who were more risk averse in the social context exhibited decreased risk-related activity in the **amygdala** during non-social decisions, while individuals who were more risk averse in the non-social context exhibited the opposite pattern. ▪ Differential risk preferences were similarly associated with hemodynamic activity in **ventral striatum** at the outcome of these decisions.

Table A1. Overview of fMRI Studies and Corresponding Neural Correlates of Trust

Mattavelli, Andrews, Asghar, Towler, & Young (2012)	20 (10/10) / faces	Neuropsychological and neuroimaging studies have demonstrated a role for the amygdala in processing the perceived trustworthiness of faces, but it remains uncertain whether its responses are linear (with the greatest response to the least trustworthy-looking faces), or quadratic (with increased fMRI signal for the dimension extremes). It is also unclear whether the trustworthiness of the stimuli is crucial or if the same response pattern can be found for faces varying along other dimensions. In addition, the responses to perceived trustworthiness of face-selective regions other than the amygdala are seldom reported.	▪ Results show neural responses to computer-manipulated trustworthiness in the **amygdala** and core face-selective regions in the **occipital** and **temporal lobes**. ▪ The authors asked whether the activation pattern is specific for differences in trustworthiness or whether it also tracks variation along an orthogonal male–female gender dimension. ▪ The main findings were quadratic responses to changes in both trustworthiness and gender in all regions. ▪ These results are consistent with the idea that face-responsive brain regions are sensitive to face distinctiveness and the social meaning of the face features.
Phan, Sripada, Angstadt, & McCabe (2010)	36 (22/14) / trust game with unique reputational manipulation	Brain reward circuitry, including ventral striatum and orbitofrontal cortex, has been independently implicated in preferences for fair and cooperative outcomes as well as learning of reputations. Using fMRI and a "trust game" task involving iterative exchanges with fictive partners who acquire different reputations for reciprocity, the authors measured brain responses in 36 healthy adults when positive actions (entrust investment to partners) yield positive returns (reciprocity) and how these brain responses are modulated by partner reputation for repayment.	▪ Volunteers chose to trust cooperative more often than uncooperative, neutral, and computer partners. ▪ Volunteers perceived cooperative partners to be more "trustworthy" than uncooperative and neutral partner, based on subjective ratings collected after fMRI scan. ▪ Results show that positive reciprocity robustly engaged the **ventral striatum** and **orbitofrontal cortex**. ▪ Moreover, this signal of reciprocity in the **ventral striatum** appeared selectively in response to partners who had consistently returned the investment (e.g., a reputation for reciprocity) and was absent for partners who lack a reputation for reciprocity. ▪ These findings elucidate a fundamental brain mechanism, via reward- related neural substrates, by which human cooperative relationships are initiated and sustained.
Poore et al. (2012)	17 (9/8) / partners in a romantic relationship	Investigation on the question of whether implicit social reward processing meaningfully contributes to explicit social representations such as trust and attachment security in pre-existing relationships. Examination of reward system prediction-error activity in response to a potent social reward – social validation – and this activity's relation to both attachment security and trust in the context of real romantic relationships.	▪ Results indicate that activity for **mid-brain** and **striatal reward** system regions of interest was modulated by social reward expectation violation in ways consistent with prior research on reward prediction-error. ▪ Additionally, activity in the **striatum** during viewing of disconfirmatory information was associated with both increases in post-scan reports of attachment anxiety and decreases in post-scan trust, a finding that follows directly from representational models of attachment and trust.

Table A1. Overview of fMRI Studies and Corresponding Neural Correlates of Trust

Riedl et al. (2010b)	20 (10/10) / eBay websites	Research provides increasing evidence that women and men differ in their decisions to trust. However, information systems research does not satisfactorily explain why these gender differences exist. One possible reason is that, surprisingly, theoretical concepts often do not address the most obvious factor that influences human behavior: biology. The goal of the study was to show empirically that gender differences in online trust are associated with gender-specific activity changes in certain brain areas	▪ Results show that most of the brain areas that encode trustworthiness differed between women and men. ▪ Moreover, women activated more brain areas than did men. These results confirm the empathizing–systemizing theory, which predicts gender differences in neural information processing modes. For trustworthy vs. untrustworthy offers: ▪ There was significantly higher brain activation in women in the **thalamus**, **striatum (putamen)**, and **fusiform gyrus** (BA 37). ▪ In contrast, there was higher activation in men only in the **DLPFC** (BA 9). ▪ Furthermore, results show increased activation in the **dorsal ACC** (BA 32) in both women and men, although the cluster size (in voxels) was much larger in men. Moreover, the authors found increased activation in the **lingual gyrus** and **cuneus** (BA 18) for both genders. For untrustworthy vs. trustworthy offers: ▪ Results show significantly higher brain activation for women in the **ventral ACC** (BA 24), **hippocampus**, **DLPFC** (BA 9), and **caudate nucleus** (body). ▪ In contrast, results show higher activation for men in the **VMPFC** (BA 10) and **ventral posterior cingulate cortex** (BA 23). ▪ Moreover, the authors found increased activation in the **insular** cortex, with exactly the same cluster size, in both women and men.
Riedl et al. (2014), Riedl et al. (2011)	18 (7/11) / trust game with avatar faces und human faces	It is hypothesized that in trust situations, people will perceive human faces differently than they will perceive avatar faces. This prediction is based on evolution theory, because throughout human history the majority of interaction among people has taken place in face-to-face settings. Therefore, unlike perception of an avatar face, perception of a human face and the related trustworthiness discrimination abilities must be part of the genetic makeup of humans. Against this background, a functional MRI experiment based on a multiround trust game was conducted (to gain insight into the differences and similarities of interactions between humans versus human interaction with avatars).	Results indicate that: ▪ People can better predict the trustworthiness of humans than the trustworthiness of avatars. ▪ Decision making about whether or not to trust another actor activates the **medial frontal cortex** significantly more during interaction with humans if compared to interaction with avatars; this brain area is of paramount importance for predicting other individuals' thoughts and intentions (mentalizing), a notably important ability in trust situations. ▪ The trustworthiness learning rate is similar whether interacting with humans or avatars.

Table A1. Overview of fMRI Studies and Corresponding Neural Correlates of Trust

Smith-Collins et al. (2013)	24 (24/0) / trust game	Previous studies have identified brain regions engaged by decision making during social encounters, but the mechanisms supporting modification of future behavior by utilizing social experience are not well characterized. Using fMRI, the authors show that cooperation and betrayal during social exchanges elicit specific patterns of neural activity associated with future behavior.	▪ Unanticipated cooperation led to greater behavioral adaptation than unexpected betrayal and was signaled by specific neural responses in the **striatum** and **midbrain**. ▪ More specifically, neural responses to outcomes, following investment decisions in series one, differentiated between expected vs. unexpected partner responses. This contrast highlighted greater activity in the **right ventral striatum** in response to trustee actions corresponding to investor expectations. ▪ The authors focused on how neural activity in response to the outcome of a trust decision with a particular partner in series one related to what trust decision would be made when encountering that partner again in series two. ▪ However, contrasting only series, where participant invested again (suggesting reinforcement of the investment response) with series, where participant did not invest (no evidence of reinforcement), trials showed that successful reinforcement was associated with increased regional activity in the **right ventral striatum** and **mid-frontal gyrus**. ▪ Appropriate behavioral adaptation in the second series of trust games was associated with specific neural responses to unexpected outcomes in the first series of games. Brain regions in which these adaptation effects were evident included **dorsal striatum**, **anterior cingulate cortex** (ACC), **right dorsolateral prefrontal cortex** (DLPFC), **left OFC** and the **midbrain** in the region of the **substantia nigra**. ▪ Region-of-interest analysis of parameter estimates revealed that activity in some brain areas, notably the **midbrain**, was only associated with successful vs. unsuccessful adaptation following UC trials. ▪ Other regional neural activity, such as that in **dorsal ACC**, was associated with successful adaptation following both UC and UB by trustee partners.
Stanley et al. (2012)	40 (22/18) / trust game	The striatum and amygdala have been identified as regions of the brain involved in trust decisions and trustworthiness estimation, respectively. However, it is unknown whether social reputation based on group membership modulates the involvement of these regions during trust decisions.	▪ At the time of choice, baseline BOLD responses in the **striatum** correlated with individuals' trust bias—that is, the overall disparity in decisions to trust Black versus White partners. ▪ BOLD signal in the **striatum** was higher when deciding to trust partners from the race group that the individual participant considered less trustworthy overall. ▪ In contrast, activation of the **amygdala** showed greater BOLD responses to Black versus White partners that scaled with the amount invested. ▪ These results suggest that the **amygdala** may represent emotionally relevant social group information as a subset of the general detection function it serves, whereas the **striatum** is involved in representing race-based reputations that shape trust decisions.
Van den Bos, van Dijk, Westenberg, Rombouts, & Crone (2009)	22 (11/11) / trust game	Examination of the neural correlates of reciprocity by manipulating two factors that influence reciprocal behavior: (1) the risk that the trustor took when trusting and (2) the benefit for the trustee when being trusted.	▪ Results showed that **anterior medial prefrontal frontal cortex** (aMPFC) was more active when participants defected relative to when participants reciprocated but was not sensitive to manipulations of risk and benefit or individual differences in social value orientation (SVO). ▪ However, activation in the **temporal-parietal-junction** (rTPJ), **bilateral anterior insula** and **anterior cingulate cortex** (ACC) was modulated by individual differences in SVO. ▪ In addition, these regions were differentially sensitive to manipulations of risk for the trustor when reciprocating. ▪ In contrast, the **ACC** and the **right dorsolateral prefrontal cortex** were sensitive to the benefit for the trustee when reciprocating.

Table A1. Overview of fMRI Studies and Corresponding Neural Correlates of Trust

Van den Bos, van Dijk, & Crone (2012)	54 (27/27) / trust game	Investigation of the neural correlates of social behavior during three phases of adolescence, carrying out fMRI of participants' brains while they were Player 2 in the Trust Game.	▪ With age, adolescents were increasingly sensitive to the perspective of the other player as indicated by their reciprocal behavior. ▪ These advanced forms of social perspective-taking behavior were associated with increased involvement of the **left temporoparietal junction** and the **right dorsolateral prefrontal cortex**. ▪ In contrast, young adolescents showed more activity in the **anterior medial prefrontal cortex**, a region previously associated with self-oriented processing and mentalizing.
Wardle et al. (2013)	31 (20/11) / trust game	The ability to initiate and sustain trust is critical to health and well-being. Willingness to trust is in part determined by the reputation of the putative trustee, gained via direct interactions or indirectly through word of mouth. Few studies have examined how the reputation of others is instantiated in the brain during trust decisions. Here the authors use an event-related fMRI-- design to examine what neural signals correspond to experimentally manipulated reputations acquired in direct interactions during trust decisions.	▪ The authors show that the **caudate** (both left and right) signaled reputation during trust decisions, such that the **caudate** was more active to partners with two types of "bad" reputations—either indifferent partners (who reciprocate 50% of the time) or unfair partners (who reciprocate 25% of the time)—than to those with "good" reputations (who reciprocate 75% of the time). ▪ Further, individual differences in **caudate** activity related to biases in trusting behavior in the most uncertain situation (i.e., when facing an indifferent partner). ▪ The area identified in the **right middle temporal gyrus**, similar to the caudate, was more active to indifferent and unfair partners, compared to fair. ▪ The **right cerebellum** demonstrated a similar pattern of greater activity to indifferent and unfair partners, but this activity was moderated by eventual investment decision such that increased activity to "bad" partners in the cerebellum was more evident when participants chose keep than when they chose invest. ▪ The **right precentral gyrus** showed the same pattern as the **cerebellum**, with increased activity to "bad" partners that appeared primarily when the participant chose keep. ▪ The left and **right inferior parietal lobules** were both more active to indifferent and unfair compared to fair, with no moderation of this effect by eventual investment decision. ▪ Finally, the **right cuneus** displayed the most complex partner x choice interaction. Here, when the participant chose to invest, activity was similar to fair and indifferent partners, but actually declined significantly to unfair partners.
Watabe, Ban, & Yamamoto (2011)	21 (0/21) / statements about person´s behavior	Investigation of how information about others' trustworthiness affects brain region activation in a fMRI study.	▪ Results show that making trustworthiness judgments when reading relevant statements was associated with differential activation in five regions: the **angular gyrus** (AG), **anterior cingulate** (AC), **left frontal lobe** (LF), **right frontal lobe** (RF), and **putamen/caudate nucleus** (PU/CA). ▪ Previous study using a highly abstract economic game situation has also shown activation in these regions. ▪ In addition, results show that people with high or low scores on a general trust scale showed less activation than did people with middle-range scores. ▪ These results suggest that the participants used trial-and-error learning to decide whether to trust others, and that this learning history (represented here as general trust level) influenced automatic processing of new trust judgments.

Appendix B: General Group Analysis

Step 1: General Group Analysis

Procedure

In the general group analysis, one investigates relevant brain regions that are associated with increasing or decreasing values of trustworthiness shares, which provides the basis for the following PPI analysis. The procedure of the general group analysis—a contrast-based analysis[5]—is in line with current neuroIS studies (see, e.g., Dimoka, 2010; Kopton et al., 2013; Riedl et al., 2010b, 2014b). For the first-level analysis, we estimated a general linear model (GLM1)[6] for each participant, with robust weighted least squares (rWLS) (Diedrichsen & Shadmehr, 2005) with the following independent variables: (R1) an onset regressor for all trustworthiness classes (A, B, C, D, E); (R2) a parametric modulator for the averaged trustworthiness share for each stimulus (aTS; equals the averaged sample mean for each stimuli based on the individual trustworthiness share for each stimulus (indTS))[7]; and (R3–R9) movement regressors and session constant. We modeled the regressors capturing each trustworthiness class (R1) using a box car function with the individual response time as duration. We convolved each of the regressors with a canonical hemodynamic response function (HRF) (Friston et al., 1995; Huettel et al., 2009). For each participant, we calculated two first-level single-subject contrasts of interest: 1) activation in brain regions that positively correlates with aTS (R2+); and 2) activation in brain regions that negatively correlate with aTS (R2-). On the group level (second level), we computed a one-sample t-test over all subjects and generated statistical parametric maps for the given contrasts (R2+, R2-) that displayed the t-value for each peak voxel that met a $p < .001$ (uncorrected) significance level with an extent threshold voxel of $k = 5$.

Results

With increasing values for aTS, we identified, among others, a significant main cluster in the bilateral caudate nucleus, especially a part of the dorsal striatum, the bilateral lingual, and the middle temporal gyrus. With decreasing values for aTS, we identified, among others, significant main clusters in the right inferior frontal gyrus, the left ventral anterior cingulate gyrus, and the left medial frontal gyrus (see Table B1 for results and Figure B1a-d for visualization of brain regions).

In line with neuroscientific research on trust processes (see Table A1) and existing procedures of meuroIS that analyze fMRI data by using different contrasts (Dimoka, 2012), we found similar activation patterns in regions associated with limbic structures (i.e., the anterior cingulate cortex (Baumgartner et al., 2008; Bereczkei et al., 2013; Bos et al., 2009; King-Casas et al., 2005), prefrontal brain areas (i.e., orbitofrontal cortex (oFC) and dorsolateral prefrontal cortex (dlPFC)) (Aimone et al., 2014; Baumgartner et al., 2008; Bos et al., 2009; Delgado et al., 2005; King-Casas et al., 2005; Krueger et al., 2007; Winston et al., 2002), and major structures of the striatum, such as the putamen and caudate (Baumgartner et al. 2008; Delgado et al., 2006; Fareri et al., 2012; Phan et al. 2010).

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[5] A contrast-based analysis statistically compares the activation evoked by two or more experimental conditions; one conducts the comparison to test a hypothesis (Huettel et al., 2009, p. 519).
[6] A general linear model (GLM) is a group of statistical tests that assume that the data comprise the linear combination of different model factors along with uncorrelated noise (Huettel et al., 2009, p. 522).
[7] The averaged trustworthiness share is the sum of each individual trustworthiness share for a specific stimulus (i.e., A1) divided by the number of all participants.

Table B1. Main Results for General Group Analysis

Main results of brain cluster positively correlated with aTS

Region	Side	No. of voxels	BA	MNI Coordinates (x, y, z)	Peak intensity (T-value)	Region	Side
Caudate body	R	145		8	16	Caudate body	R
Middle frontal gyrus	L	15	8	-30	38	Middle frontal gyrus	L
Insula	R	20	13	44	-20	Insula	R
Cingulate gyrus	R	5		8	-8	Cingulate gyrus	R
Lingual gyrus	L	44	17	-18	-94	Lingual gyrus	L
Lingual gyrus	R	42	17	18	-92	Lingual gyrus	R
Lingual gyrus	L	14	19	-16	-66	Lingual gyrus	L
Middle temporal gyrus	R	47	21	56	-10	Middle temporal gyrus	R
Precentral gyrus	R	11	3/4	50	-14	Precentral gyrus	R
Postcentral gyrus	R	313	2	44	-38	Postcentral gyrus	R
Postcentral gyrus	R	58	7	22	-52	Postcentral gyrus	R

Main results of brain cluster negatively correlated with aTS

Region	Side	No. of voxels	BA	MNI Coordinates (x, y, z)	Peak intensity (T-value)	Region	Side
Cingulate gyrus (Figure B1a)	L	36	24	-2	-10	*Cingulate gyrus (Figure B1a)*	L
Medial frontal gyrus (Figure B1b)	L	37	8/32	-4	24	*Medial frontal gyrus (Figure B1b)*	L
Inferior frontal gyrus (Figure B1c)	R	211	8/9	52	14	*Inferior frontal gyrus (Figure B1c)*	R
Middle frontal gyrus	L	46	46	-44	38	Middle frontal gyrus	L
Inferior frontal gyrus	L	97	11/47	-46	42	Inferior frontal gyrus	L
Inferior frontal gyrus/Insula	L	49	45/13	-44	16	Inferior frontal gyrus/Insula	L
Inferior frontal gyrus	R	98	45	58	20	Inferior frontal gyrus	R
Postcentral gyrus	L	14		-52	-20	Postcentral gyrus	L
Inferior parietal lobule	L	1887	40	-44	-38	Inferior parietal lobule	L
Inferior parietal lobule	R	75		36	-64	Inferior parietal lobule	R

Height threshold T = 3.5794, p < 0.001 [uncorrected], k = 5
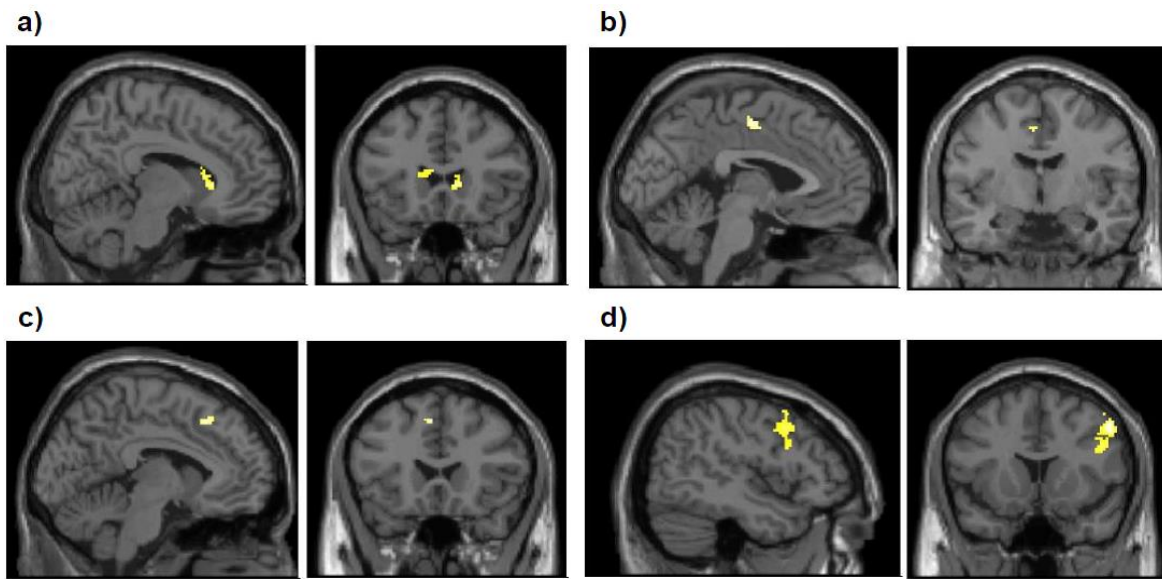
Figure B1. Activity for Increasing aTS in A) Caudate Nucleus and For Decreasing aTS In B) Ventral Anterior Cingulate Gyrus, C) Dorsal Anterior Cingulate Gyrus and D) Dorsolateral Prefrontal Cortex (see Table 1)

Appendix C: Overview of PPI Analysis

Table C1. Overview of PPI Analysis for dlPFC, cACC, and dACC as Seed Regions

Regions showing positive task-related functional connectivity with the anterior cingulate gyrus (BA 32)

Region	Side	No. of voxels	BA	MNI Coordinates	Peak intensity (T-value)	Region	Side
Lingual gyrus	R	77		8	-76	Lingual gyrus	R
Parahippocampal gyrus	R	48	19	36	-46	Parahippocampal gyrus	R
Cerebellum anterior Lobe	L	110		-8	-56	Cerebellum anterior Lobe	L
Superior temporal gyrus	L	12	22	-46	-6	Superior temporal gyrus	L
Parahippocampal gyrus	L	45		-20	-36	Parahippocampal gyrus	L
Insula	R	12	13	42	-10	Insula	R
Middle frontal gyrus	R	61	10/46	-26	50	Middle frontal gyrus	R
Inferior frontal gyrus	R	16	9	56	10	Inferior frontal gyrus	R
Inferior parietal lobule	R	49	40	34	-54	Inferior parietal lobule	R
Precuneus	R	24		12	-56	Precuneus	R
Superior frontal gyrus	R	179	6	12	2	Superior frontal gyrus	R
Superior frontal gyrus	L	34	6	-10	-2	70	3.53

Regions showing negative task-related functional connectivity with the anterior cingulate gyrus (BA 32)

Middle temporal gyrus	L	42	19	-40	-84	18	-4.06

Regions showing positive task-related functional connectivity with the anterior cingulate gyrus (BA 24)

Region	Side	No. of voxels	BA	MNI Coordinates	Peak intensity (T-value)	Region	Side
Middle frontal gyrus	R	12	10	46	48	Middle frontal gyrus	R
Inferior frontal gyrus	R	76	9	60	10	Inferior frontal gyrus	R
Superior frontal gyrus	L	73	9	-30	38	Superior frontal gyrus	L
Precuneus	R	13	7	20	-50	Precuneus	R
Regions showing negative task related functional connectivity with the anterior cingulate gyrus (BA 24)						Regions showing negative task related functional connectivity with the anterior cingulate gyrus (BA 24)	

Regions showing positive task-related functional connectivity with the right inferior frontal gyrus (BA 9)

Hippocampus	R	112		28	-40	2	4.29
Inferior frontal gyrus	L	24	44	-58	6	18	4.02
Caudate body	L	63		-8	-6	22	4.71
Superior frontal gyrus	L	64	6	-14	14	68	3.55
Superior frontal gyrus	L	72	6	-10	-6	72	3.97

Regions showing negative task-related functional connectivity with the right inferior frontal gyrus (BA 9)

Medial frontal gyrus	L	40	10	-2	44	-8	-3.72

Table C1. Overview of PPI Analysis for dlPFC, cACC, and dACC as Seed Regions

Middle temporal gyrus	R	19	21	48	4	-30	-3.18
Inferior occipital gyrus	L	20	19	-40	-78	-10	-3.29
Middle temporal gyrus	R	146	39/22	46	-64	22	-4.65
Middle temporal gyrus	L	59	19	-38	-84	16	-4.39
Angular gyrus	R	105	39	40	-80	30	-4.18
Superior occipital gyrus	L	20	19	-38	-82	30	-3.68
Superior frontal gyrus	L	20	9	-16	54	38	-5.63
Middle frontal gyrus	L	24		-24	6	48	-4.07
Cingulate gyrus	L	14	31	-16	-24	36	-4.38

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