MIS Quarterly

RESEARCH ARTICLE

AN fMRI EXPLORATION OF INFORMATION PROCESSING IN ELECTRONIC NETWORKS OF PRACTICE[1]

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Online forums sponsored by electronic networks of practice have become an important source of information for individuals seeking solutions to problems online. However, not all information available in a forum is helpful or accurate, requiring knowledge seekers to evaluate and filter the solutions they encounter. Most forums offer contextual cues to help knowledge seekers make evaluation decisions, yet little is understood about the cognitive processes and neural mechanisms that underlie how information on these forums is filtered and evaluated. This paper draws on literature in cognitive neuroscience and NeuroIS to develop exploratory research questions about the role of both content and contextual cues in forum filtering tasks, the comparative and interactive effects of different types of contextual cues, and the neural functions associated with filtering processes. These questions are explored using an fMRI experimental study that captured forum information filtering behaviors and measured the neural correlates involved in evaluating both solution content and contextual cues. Results show that both content and contextual cues influence final filtering decisions, with community-based cues factoring more heavily than expert-based cues. Moreover, we observe distinct neural activation patterns when forum knowledge seekers encounter certain cue combinations. Based on our observations, we derive a theoretical model comprising testable research propositions about both behavioral and neural facets of forum information filtering.

Keywords: fMRI, electronic network of practice, information filtering, online forum, programming experiment

[1]James Thong was the accepting senior editor for this paper. Eric Walden served as the associate editor.

The appendices for this paper are located in the "Online Supplements" section of *MIS Quarterly*'s website (https://misq.org).

Introduction

> hello, my fuel pump will not turn on when the ignition key is in on position. relays and fuses are fine. the thing is when it decides to work, truck starts and runs great. it will be ok for a day or 10 days. park it in the driveway but the pump will not activate so it will not start the next morning. this has happened 3 times in the past month. please help. thank you! (https://community.cartalk.com/t/fuel-pump-issues/42922)

> Recently I bought some dark roasted coffee, but it turned out the roast wasn't dark enough for my taste. While sipping the insipid brew, I asked myself, 'Why can't I take these beans and roast them some more?' Now I'm asking you, the coffee mavens. Can this be done? And how might be the best way to do it? Thanks! (http://www.cheftalk.com/t/59866/re-roasting-coffee-beans-can-it-be-done)

> I am having trouble figuring out where to get started in this proof. Let πi be the inclusion probability of unit i in some sample scheme for drawing n units out of a population of size N. How can I go about showing that the sum of all πi for i from 1 to N is equal to the sample size n? Any help would be appreciated. (http://mathhelpforum.com/statistics/239922-proving-sum-inclusion-probabilities-equals-sample-size-n.html)

Every day, people all over the world ask millions of questions like these. To whom are these questions addressed? Although some are directed to family, friends, or trusted experts, a vast and growing proportion (including the three examples above) are posed to the masses via internet-enabled platforms that support networks of individuals with shared interests or information needs. Termed *electronic networks of practice*, these networks comprise a set of loosely affiliated individuals who share a common practice and communicate via technology-mediated channels (Wasko and Faraj 2005). Electronic networks of practice have become a primary information source for millions of knowledge seekers, with topics ranging from animals and automotive to finance and food to technology and travel, just to name a few ("The Biggest Boards" 2017).

One of the most common tools used by an electronic network of practice (hereafter simply *network)* is the online knowledge forum, a virtual bulletin board where network participants can post and retrieve knowledge about topics relevant to their shared practice. Research indicates that network forums are important sources of knowledge for both individuals and firms (Beck et al. 2014). Forums are popular tools among network participants because they support knowledge exchange centered on problem solving (Meyer-Gossner 2013). For example, software developers searching for a solution to a programming problem might access an online forum such as stackoverflow.com or dreamincode.net to request information from other network participants or to search for existing queries that match their own. In response, other network participants post potential solutions, often in the form of actual code blocks. Surrounding these solutions, most forums offer additional contextual cues to the information seeker, such as characteristics of the respondent (e.g., expertise level), endorsement of the solution by an expert participant, or validation of the solution by other members of the community. Therefore, individuals who turn to network forums as a knowledge source must filter and evaluate different types of information as they decide which solution(s) to ultimately adopt, a process referred to herein as *forum information filtering*.

Research has begun to explore how information on network forums is filtered by examining which cues people attend to when evaluating forum information (Meservy et al. 2014) and how attentional switching patterns among these cues affect filtering outcomes (Fadel et al. 2015). However, the actual cognitive processes that underlie how people evaluate these cues remain unclear. Do people engage in qualitatively different types of thinking as they evaluate different types of information on network forums? Do certain cues exhibit interaction effects that influence subsequent evaluation patterns? And do some types of processing lead to more accurate information filtering outcomes? Answering these questions extends our theoretical understanding beyond *what* happens during information filtering to *why* it happens, a critical step in establishing a theoretical and practical foundation for knowledge exchange via electronic networks of practice.

Explicating the cognitive processes that underlie information processing has long been an occupation of the domain of cognitive neuroscience (Anderson 1990; Gazzaniga 2004). Information Systems (IS) researchers have recognized the potential value of applying neuroscience tools and techniques to better understanding the cognitive processes that underlie IS phenomena. Known as *NeuroIS* (Dimoka et al. 2011; Riedl et al. 2014; Riedl and Léger 2016), this branch of IS research is concerned with the application of cognitive neuroscience literature and functional brain imaging tools to "further advance our knowledge of the complex interplay of IT and information processing, decision making, and behavior" (Dimoka et al. 2011, p. 687). In this paper, we report the results of an exploratory NeuroIS study aimed at better understanding the cognitive processes involved when people filter information found in online network forums. Our approach is exploratory because, to our knowledge, little research has examined forum information filtering from a neurocognitive perspective. Although some inferences may be drawn from general neuroscience research, a testable theory about the neurocognitions and behaviors involved in this type of information filtering does not yet exist. We therefore adopt a theory-building approach in which we formulate general research questions, examine experimental data associated with these questions, and use our results to infer theoretical propositions for future research. Although somewhat uncommon in the IS domain, this approach has precedent in neuroscience research (e.g., Kolling et al. 2012) and lays a conceptual foundation for future studies. Ultimately, establishing information filtering behaviors along with their neural correlates can lead to better theory and practice to support both the design of technology-mediated channels and the filtering strategies employed by those who use them.

The rest of this paper is organized as follows. First, we outline key characteristics of online network forums, including the types of cues that knowledge seekers typically encounter. We then formulate exploratory research questions about different types of cognition involved in evaluating and filtering forum solutions. We report our exploration of these questions using data collected from a functional magnetic resonance imaging (fMRI) experiment that measured neural hemodynamic response as participants completed an information evaluation task using a mock network forum. Based on our analysis, we derive a series of theoretical propositions about forum information filtering behaviors and the possible neurological mechanisms that underlie these behaviors. We conclude by discussing implications of our findings for research and practice.

Background

An electronic network of practice is formally defined as a collection of loosely affiliated individuals who form a "self-organizing, open activity system focused on a shared practice that exists primarily through computer-mediated communication" (Wasko and Faraj 2005, p. 37). Although most such networks comprise hundreds or even thousands of participants, knowledge exchange on a network forum typically occurs in the form of dyadic information exchanges between knowledge seekers and knowledge contributors. Importantly, the roles of knowledge seeker and knowledge contributor are fluid and interchangeable; a given participant may use the forum to seek knowledge in one case and to contribute expertise in another.

Unlike other commonly studied platforms of technology-mediated information exchange such as email (Sussman and Siegal 2003) or internal knowledge repositories (Fadel et al. 2009; Zhang and Watts 2008), the loose and unstructured nature of participation in a network poses several unique information processing challenges for knowledge seekers. Because queries can usually be answered by any and all network participants, knowledge seekers often face the task of evaluating several unique and possibly conflicting answers. Because seekers do not know contributors personally, they may have difficulty evaluating the expertise of the knowledge contributor and, by extension, the validity of the response. Moreover, depending on the nature of the query and the background of the knowledge seeker, it may be difficult or impossible for the seeker to evaluate the *content* of posted solutions on their own merits due to inexperience or lack of adequate technical expertise.

To assist knowledge seekers in overcoming these difficulties, forums typically offer additional *contextual* cues to help seekers evaluate the solutions they find. For example, many forums provide information about the expertise of the solution contributors, such as the total time contributors have participated in the network, the number of queries they have answered, or an expertise rating provided by forum moderators or other network participants. Contributor expertise is one type of contextual cue that has been studied in various technology-mediated information exchange contexts (Fadel et al. 2009; Sussman and Siegal 2003; Zhang and Watts 2008). However, another important cue that has received less research attention but has been shown to be even more influential in filtering decisions is *validation*: the endorsement (or lack thereof) of a solution by one or more individuals *other than the author* (Fadel et al. 2015; Meservy et al. 2014). Many forums provide a mechanism that allows subject matter experts and/or other participants to provide validation of specific solutions, such as star ratings, up/down votes, or "accepted solution" designations. Although these cues might not accurately reflect the quality of the solution content itself, they offer ancillary information to seekers to help them judge the potential validity of posted solutions and decide which, if any, to ultimately adopt. Therefore, seekers who either post their own queries to a forum or search for answers to others' queries must evaluate several potentially competing candidate solutions by examining (1) the content of the solutions themselves, (2) the contextual cues surrounding each solution, or (3) a combination of both. In this paper, our objective is to explore the cognitive differences between filtering based on these cues. Our work is situated within recent IS research that has begun to explore forum information filtering (see Appendix A for more details).

Exploratory Questions

Our inquiry into cognitions and behaviors associated with forum information filtering stems from basic observations about the nature of these forums and the types of cues therein. We enumerate these observations in this section and, consistent with our theory-building approach, identify five exploratory research questions that probe cognitions and behaviors involved in forum information filtering. These questions are organized into three overarching themes: (1) the *individual* effects of different forum elements (solution content and surrounding contextual cues), (2) the *comparative* effects of these elements in relation to each other, and (3) the *combined* effects of these elements when they are congruent/incongruent in their indications.

Individual Effects

As noted above, forum users can attend to various forum elements when evaluating a solution. These elements can be broadly categorized as consisting of either (1) the contextual cues surrounding a solution or (2) the solution content itself. Contextual cues associated with a solution offer indications that are either *positive* (i.e., favorable) or *negative* (i.e., unfavorable) toward the solution. For example, positive cues may include endorsement by an ostensible expert, a favorable ratio of up/down votes from the community, or being tagged as an accepted solution, whereas negative cues would include opposite indicators (Bhattacherjee and Sanford 2006). Evidence from the neuroscience literature suggests the possibility of distinct neural mechanisms for processing positive and negative information (for a review, see Lindquist et al. 2015); however, how and whether these mechanisms operate in the context of forum information filtering remains an open question.

> *Question 1: How does contextual cue valence (positive versus negative) affect forum information filtering decisions? Are different neural systems responsible for processing positive/negative contextual cues?*

As an alternative or supplement to contextual cues, knowledge seekers may choose to evaluate the solution content itself. According to information processing theories, content-based filtering is likely to occur only if the knowledge seeker possesses the capability and motivation to analyze the information content (Petty and Cacioppo 1986). Prior studies have shown that in other technology-mediated contexts, able and motivated knowledge seekers base their information adoption decisions primarily on the perceived quality (or lack thereof) of the information content (Sussman and Siegal 2003; Zhang and Watts 2008). Analyzing content requires careful scrutiny of the solution semantics to identify any flaws that render the solution untenable. Neuroscience research suggests that this type of content-based filtering may involve areas of the brain associated with error detection (Friederici et al. 2003), discrepancy resolution (Botvinick et al. 2004; Bush et al. 2000; Kawamoto et al. 2012), or stimulus salience (Menon 2011).

> *Question 2: How does content quality (high versus low) affect forum information filtering decisions? Are different neural systems responsible for processing high/low-quality content?*

Comparative Effects

Most information filtering judgments involve some combination of context and content, yet the relative influence of these elements can vary widely (Petty and Cacioppo 1986; Petty et al. 2005). Thus, an important theoretical question surrounding forum information filtering concerns the comparative influence of these elements on filtering judgments. First, what are the relative effects of different types of contextual cues? On network forums these cues can take various forms and originate from many sources, but can generally be categorized as *expert-based* (originating from putative domain experts) or *community-based* (originating from the larger network populace). How might these types of cues compare in their influence on filtering decisions? Research on consumer product reviews indicates that product/service consumption decisions are more heavily influenced by community-based reviews than by expert-based reviews (Dellarocas et al. 2007; Zhang et al. 2010), but whether this holds for information filtering decisions is not clear. Moreover, literature on the neuroscience of social influence suggests that different neural mechanisms may be responsible for processing different types of social cues. For example, Seiler and Walden (2016) found different neural activation patterns when decision makers were prompted with decisions of domain experts versus those of peers.

> *Question 3: Which types of contextual cues, community-based or expert-based, are more influential in forum information filtering tasks? Are different neural activation patterns associated with processing based on community- and expert-based cues?*

Second, filtering decisions can be based on a combination of contextual cues and content. Prior work has found that information content is the primary basis for judgment among knowledge seekers who are able and motivated to examine it (Fadel et al. 2009; Sussman and Siegal 2003; Zhang and Watts 2008). However, other studies in the context of network forums have found that contextual cues (specifically, validation) play a more prominent role, even among those who are capable of and motivated to assess information content (Fadel et al. 2015; Meservy et al. 2014). Although contextual cues can be quickly and readily assessed, content-based filtering requires more effortful evaluation of the solution's internal validity; thus, from a neurological perspective, one might expect greater recruitment of brain regions associated with semantic processing for content-based filtering vis-à-vis context-based filtering (Price 2010; Wagner et al. 2001).

> *Question 4: How do solution content and contextual cues compare in their influence on forum information filtering decisions? Do distinct neural processes underlie filtering based on content versus filtering based on context?*

Congruence/Incongruence Effects

Finally, different contextual cues associated with a single solution may conflict in their indications, and may or may not be consistent with the actual quality of the solution. This raises the possibility that cues may interact (either additively or diminutively) in their influence on filtering judgments. Research on digital goods consumption, for example, lends some support to this notion, finding that consistent expert- and community-based reviews had an additive effect on consumers' propensity to download and consume online software applications (Amblee and Bui 2007). On the other hand, cue disagreement may induce a state of cognitive dissonance wherein knowledge seekers must reconcile the indications of two conflicting signals and determine which (if any) they will follow. Resolving such discrepancies could invoke neural systems associated with cognitive dissonance (Izuma et al. 2010) or prediction error (Corlett et al. 2004; Garrison et al. 2013), which occurs when originally expected outcomes (e.g., expecting the solution to be high quality due to a positive contextual cue) are later violated (e.g., finding flaws in the solution upon examining its content).

> *Question 5: Do cues exert an interactive effect on information filtering decisions when they are congruent versus when they are incongruent? What neural mechanisms are involved in processing congruent versus incongruent cues?*

Methodology

To explore our research questions, we conducted a controlled fMRI experiment to observe the cognitive processing patterns that occur as people process and filter information found on online network forums. We followed guidelines established in the NeuroIS literature (vom Brocke and Liang 2014; Dimoka 2011) for conducting an fMRI study. Similar to prior research (Fadel et al. 2015; Meservy et al. 2014), we chose the domain of software development/programming as the context for our experimental task. Software development is a field oriented around problem solving and a domain in which network forums are commonly used as a knowledge source (Brandt et al. 2009; Hoffmann et al. 2007; Stylos and Myers 2006). We designed a custom experimental instrument that mimicked the structure of an online programming forum and displayed a series of programming problem solutions in a controlled sequence. Seven programming problems (one for training and six for the experimental stimuli) were selected such that they would be familiar and readily comprehensible to most programmers but also of adequate complexity to require systematic evaluation to assess the quality of a proposed solution. Eight solutions for each of the six experimental programming problems (48 total solutions) were developed based on actual forum solutions found online. Appendix B contains a description of the programming problems and solutions used.

To examine the cognitions associated with different types of information filtering, each solution consisted of both content and contextual cues. Specifically, each solution had three factors that could assume one of two levels: a rating by a purported domain expert (expert validation) showing that the solution was either endorsed by the expert (high expert validation) or lacked expert endorsement (low expert validation); a rating by participants in the network (community validation) indicating that the solution was either recommended by the majority of community members (high community validation) or not recommended by the majority of community members (low community validation); and, finally, the actual solution code (content), which was either syntactically and logically correct for solving the problem (high code quality) or manipulated to contain logic, control flow, or other errors that prevented it from solving the problem (low code quality). Each problem thus contained four high/low-quality solutions, four high/low expert validation cues, and four high/low community validation cues. These factors yielded eight unique experimental treatment conditions that were coded according to the combination of expert validation (H/L), community validation (H/L), and code quality (H/L), respectively. For example, a solution with high expert validation, low community validation, and high code quality was coded as HLH.

Each of the six programming problems had eight solutions (one for each treatment condition), producing a randomized, fully factorial experimental design with 48 unique stimuli.

The interface of the experimental instrument was modeled after actual online programming forums, and presented prospective solutions one at a time to each participant. To maximize the face validity of the instrument, interface elements were copied from actual online forums, such as the names of the experts, avatar images,[2] expert join dates, and number of posts. Appendix B contains a sample solution for one of the problems presented.

To isolate cognitive processing differences in contextual processing (evaluation based on expert and community validation) versus content processing (evaluation of the solution content itself), it was necessary to present the solutions so that each type of processing could be induced separately. We controlled the visibility of solution components by displaying each solution in two sequential phases. In the *context phase*, participants were first shown only the contextual cues with the code obscured.[3] During this phase, participants were exposed to one of four contextual cue conditions for each solution: high expert validation and high community validation (HH), high expert validation and low community validation (HL), low expert validation and high community validation (LH), or low expert validation and low community validation (LL). The code was blurred enough to require participants to make a judgment based solely on the contextual cues, but it was apparent that there was actual code associated with the proposed solution. To ensure the contextual cues were processed, participants were asked to provide a preliminary rating (on a five-point scale) indicating how likely they would be to adopt the solution based on these cues alone. After providing the preliminary rating, participants entered the *content phase*, in which the solution code was unblurred. They were then given the opportunity to provide a final rating of the solution that incorporated their analysis of the code itself. Appendix B shows an example of the stimulus screen in the context phase.

[2]Avatar images were copied from actual online forums and may have varied in complexity. For example, 34.6% of the avatars were human faces which have been shown to be more complex than simple objects and require several areas of the brain to process (Johnson 2005). To mitigate the influence of varying levels of complexity, we randomly paired the extraneous interface elements (e.g., avatars, posts, join date) in each solution set, with each participant receiving different random pairings.

[3]Alternatively, we could have shown the code first with the contextual cues blurred. However, we showed contextual cues first as previous studies have found that participants often use these cues as a way of filtering potential candidate solutions before scrutinizing content (Fadel et al. 2015; Meservy et al. 2014).

To test the experimental instrument, we conducted a pilot study with six experienced software developers. Based on their feedback, minor alterations were made to the interface and to some solutions to improve clarity of the process and the content. To ensure participants could evaluate the solution content, we recruited experienced software developers to participate in the main study. Participants were required to have at least one year of programming experience and to be proficient in Java, C#, or C++. Each participant was screened for MRI compatibility, native-English speaking, corrected-normal visual acuity, and right-handedness. Qualified participants were then scheduled for the experiment at the MRI facility. In total, 29 experienced software developers (93.1% male, average age 26.2 years, average of 4.0 years programming experience) were recruited from local companies to participate in the study.[4] Participants were compensated with either \$25 or a 3D model of their brain. Details of the experimental procedure, including experimental flow and task details, are provided in Appendix C.

Analysis and Results

We conducted two types of analysis to address our research questions. First, we used a series of ordinal mixed effects regression models to examine how participants' filtering decisions (represented by their ratings of the solutions) were related to the experimental stimuli. Mixed effects models were used because the data we collected were hierarchical, with solutions grouped by problem and each solution rated by every participant. In addition, the dependent variable of the preliminary/final rating of each solution was ordinal in nature (measured on a scale of 1 to 5, with 5 indicating the highest probability of adoption). Therefore, we selected cumulative link (ordinal) mixed model analysis to capture both fixed (solution-level) effects and random (grouping) effects due to participants, problems, and solutions. Because each participant rated every solution for every problem, a fully-crossed random effects design was used. To perform the analysis, we used the cumulative link mixed models (CLMM) function of the ordinal package in R (Christensen 2015; R Core Team 2017) to estimate ordinal mixed effects regression models with both fixed and random effects. Appendix D provides additional details on the suitability of this approach for our data.

Models were built using data from both the context and content experimental phases. During the context phase, participants were shown only the contextual cues of expert validation (EV) and community validation (CV) and were asked to

[4]Typical sample sizes in NeuroIS fMRI studies range from 15 to 25 participants (Riedl et al. 2011).

provide a preliminary rating (PR) based on these cues. During the content phase, participants were shown the actual solution code (along with the same contextual cues) and had the opportunity to change their preliminary rating to a final rating (FR) based on their assessment of the code quality (CQ).[5] We therefore specified a series of ordinal regression models as shown in Table 1.

The second type of analysis we conducted focused on the fMRI data of participants' cognitions during the experimental task. Imaging data were analyzed using the Analysis of Functional Neuroimages (AFNI) suite of programs, version AFNI_18.1.18 (Cox 1996) and the Advanced Normalization Tools (ANTs) (Avants et al. 2008; Klein et al. 2009). All MRI imaging was done on a 3T Siemens TIM Trio scanner using a 12-channel head coil. Structural MRI scans were collected using a T1-weighted magnetization-prepared rapid acquisition with gradient echo (MP-RAGE) sequence with the following parameters: TR = 1900ms; TE = 2.26ms; 176 1-mm thick slices (no gap); acquisition matrix = 256 × 215; field of view = 218 × 250mm; voxel size = .97 × .97 × 1mm. Functional images were collected using an echo-planar imaging (EPI) sequence with the following parameters: TR = 2500ms; TE = 28ms; flip angle = 90°; 43 3-mm thick slices (no gap); acquisition matrix = 64 × 64; field of view = 192 × 192; voxel size = 3 × 3 × 3mm. We collected two functional runs of 324 volumes (TRs) each (13min 30sec per scan run).

We followed standard fMRI practices when analyzing neural data (Dimoka 2011). Functional MRI data were slice-time corrected and motion corrected to align with the middle volume of each run. The second functional run was then aligned with the first volume of the first run. Individual-level regression analyses were conducted to fit the ideal hemodynamic response to the neural data for each voxel. Parameter estimates (i.e., betas) from these individual-level models were then blurred and normalized to MNI space so that group-level analyses could be conducted using multivariate modeling to answer the neural-related exploratory questions. Appendix E contains additional details of the fMRI analysis, including a description of the individual-level analyses that were subsequently used for the group-level analyses reported below.

Results

Influence of Contextual Cue Valence

> *Question 1: How does contextual cue valence (positive versus negative) affect forum information filtering decisions? Are different neural systems responsible for processing positive/negative contextual cues?*

To explore how contextual cue valence (positive versus negative) influences filtering judgments, we conducted ordinal regression analyses for the context phase. Table 2 shows the reported effects of the contextual cue variables for a baseline model (1.0), main effects-only model (1.1), and a fully specified model (1.2).

For each of the independent variables specified in our model, we calculated the odds ratio as a measure of effect size. In ordinal regression models, the odds ratio indicates the factor by which odds of the dependent variable moving from one level to the next increases or decreases for every one-unit increase in the independent variable. For instance, an odds ratio of 2 would indicate that, *ceteris paribus*, a one-unit increase in the associated independent variable (e.g., community validation) would double the odds that the dependent variable (e.g., final rating) takes on the next ordinal value (e.g., moves from 3 to 4). Thus, the odds ratio provides an intuitive and interpretable measure of the practical effect the independent variables as well as a means for comparing their relative effect sizes.

Model 1.1 results show that both expert validation ($\beta = 1.89$, $p < .001$) and community validation ($\beta = 4.78$, $p < .001$) had a significant effect on the preliminary rating; the odds of a higher rating increased when expert and community validation were positive in valence.

To explore the neural systems responsible for processing positive and negative contextual cues, we performed repeated-measures analyses using AFNI program 3dMVM, with participant as a random factor and the factorial combinations of expert and community validation levels (HH, HL, LH, and LL) as a fixed factor. Models investigated the main effect of expert validation valence (HH and HL versus LH and LL), the main effect of community validation valence (HH and LH versus HL and LL), and the direct comparison of consistent positive valence and consistent negative valence (HH versus LL). Each of these models failed to reveal any significant clusters of activation; thus, our exploratory analysis did not find support for distinct neurocognitive processing associated with valence of contextual cues.

[5]Because information processing theories stipulate that motivation is a necessary condition for processing of content, we assessed participants' motivation in the post-survey using three main questions. These questions were answered using a seven-point scale ranging from *not at all* (1) to *a great deal* (7). Motivation questions: During your participation in the study, to what extent were you (a) trying hard to evaluate the quality of each solution presented (mean: 4.97; SD: 1.00); (b) motivated to correctly evaluate the quality of each solution presented (mean: 5.17; SD: 1.00); (c) putting forth effort to evaluate the quality of each solution presented (mean: 5.23; SD: 0.83). The results suggest that participants were sufficiently motivated to correctly complete the experimental task.

Table 1. Ordinal Regression Models	
Context Phase Models	• Model 1.0: Random Effects (participant and solution) → PR[†] • Model 1.1: EV + CV → PR • Model 1.2: EV + CV + [EV x CV] → PR
Content Phase Models	• Model 2.0: Random Effects (participant and solution) → FR • Model 2.1: EV + CV + CQ → FR • Model 2.2: EV + CV + CQ + [EV x CV x CQ]→ FR

Notes: EV = Expert Validation, CV = Community Validation, PR = Preliminary Rating, CQ = Code Quality, FR = Final Rating; Model 2.2 includes all two-way interactions between EV, CV, and CQ.
[†]Random effects were also included in each subsequent model.

Table 2. Context Phase Models

	Model 1.0	Model 1.1		Model 1.2	
Fixed Effects Variables		**Estimate (SE)**	**Odds Ratio**	**Estimate (SE)**	**Odds Ratio**
Expert Validation (EV)		1.89*** (.12)	6.62	1.71*** (.16)	5.53
Community Validation (CV)		4.78*** (.17)	119.10	4.60*** (.20)	99.97
EV × CV				.39 (.24)	1.47
Log Likelihood	2143.77	1460.23***		1458.91	
AIC	4299.54	2936.45		2935.82	
N (ratings)	1,392	1,392		1,392	
N (solutions)	48	48		48	
N (participants)	29	29		29	

*p < .05; **p < .01; ***p < .001
Notes: All models included random intercept effects for solution and participant. Log likelihood significance values indicate whether the LR test was significant from one model to the next.

Influence of High Versus Low Content Quality

Question 2: How does content quality (high versus low) affect forum information filtering decisions? Are different neural systems responsible for processing high/low-quality content?

To inspect how the quality of the content (i.e., quality of the code) impacts overall judgments of solution as a whole, we conducted ordinal regression analyses for the content phase. These models also included expert validation and community validation, which were visible during both the context and content phase. Table 3 shows the reported effects, including the ordinal regression coefficients and associated odds ratios, of the explanatory variables for a baseline model, main effects-only model, and a fully specified model.

As shown in the results for model 2.1, code quality had a significant influence on the final rating ($\beta = 2.46$, $p < .001$), providing support for the notion that participants were influenced by the actual quality of the underlying solution. In fact, solutions with high code quality had 11.69 times greater odds of receiving a higher final rating than solutions with low code quality. The influence of contextual cues also remained significant in this model, though their effect sizes were smaller.

To explore whether distinct patterns of neural activation occur when knowledge seekers evaluate high-quality solutions as opposed to low-quality solutions, we performed a repeated-measures analysis contrasting activity in the content phase for trials that received a high final rating with trials that received a low final rating, controlling for the effect of context cues by collapsing across all levels of these cues.[6] We observed three significant clusters of activation where activity differentiated between high and low final ratings (see Table 4). Large clusters in the left and right anterior insula were more active for solutions receiving a high final rating (see Appendix F).

[6]A Pearson chi-squared test of independence showed that final participant ratings were highly correlated with the high and low experimental conditions for code quality ($\chi^2 = 401.52$, $p < 0.001$) in the content phase. (Similar results were found for expert rating ($\chi^2 = 166.48$, $p < 0.001$) and community rating ($\chi^2 = 886.66$, $p < 0.001$) in the context phase.) A direct comparison between models of neural activation based on subjective quality ratings versus objective quality ratings did not reveal any significantly different activations.

Table 3. Content Phase Models

	Model 2.0	Model 2.1		Model 2.2	
Fixed Effects Variables		**Estimate (SE)**	**Odds Ratio**	**Estimate (SE)**	**Odds Ratio**
Expert Validation (EV)		.31** (.10)	1.36	.45 (.24)	1.57
Community Validation (CV)		1.13*** (.11)	3.10	1.25*** (.23)	3.48
Code Quality (CQ)		2.46*** (.21)	11.69	2.65*** (.29)	14.10
EV × CV				-.31 (.32)	.73
EV × CQ				-.44 (.31)	.64
CV × CQ				-.42 (.30)	.66
EV × CV × CQ				1.01* (.43)	2.74
Log Likelihood	1892.99	1801.76***		1798.10	
AIC	3797.97	3621.52		3622.2	
N (ratings)	1,392	1,392		1,392	
N (solutions)	48	48		48	
N (participants)	29	29		29	

*p < .05; **p < .01; ***p < .001

Notes: All models included random intercept effects for solution and participant. Log likelihood significance values indicate whether the LR test was significant from one model to the next.

Table 4. Cluster Characteristics in the High Final Rating Versus Low Final Rating Contrast

		Peak Voxel			High FR > Low FR	
	#Voxels	**X**	**Y**	**Z**	**t(28)**	***p*-value**
R. Anterior Insula	108	50	23	-8	4.558	<.001
L. Anterior Insula	97	-47	23	-11	4.952	<.001

Notes: As an indication of the size of the effect within each significant cluster, we provide t-test statistics, which reflect the mean activation difference between conditions collapsed across all voxels in the cluster.

Comparative Effects of Community-Based Versus Expert-Based Contextual Cues

> *Question 3: Which types of contextual cues, community-based or expert-based, are more influential in forum information filtering tasks? Are different neural activation patterns associated with processing based on community- and expert-based cues?*

Consistent with the literature presented earlier, Table 2 reveals that the effects of community validation (β = 4.78, 95% CI = 4.45, 5.11) were stronger than those of expert validation (β = 1.89, 95% CI = 1.65, 2.13) as evidenced by the nonoverlapping 95% confidence intervals of the regression coefficients (Cumming 2009). Holding expert validation constant, a solution with high community validation had 119.1 times higher odds of receiving a higher final rating than a solution with low community validation. Holding community validation constant, the odds of a solution with high expert validation receiving a higher final rating were 6.62 times higher than those of a solution with low expert validation.

To examine the question of whether different neural activation patterns are associated with processing based on community- and expert-based cues, we contrasted trials where the expert rating was high and the community rating was low (HL) with trials where the expert rating was low and the community rating was high (LH). This contrast did not yield any significant activation differences.

Comparative Effects of Content Versus Contextual Cues

> *Question 4: How do solution content and contextual cues compare in their influence on forum information filtering decisions? Do distinct neural processes underlie filtering based on content versus filtering based on context?*

Comparing the 95% confidence intervals of the regression coefficients in model 2.1 (Table 3) shows that the influence of content quality on the final ratings (β = 2.46, 95% CI = 2.04, 2.88) was stronger than that of community validation (β = 1.13, 95% CI = 0.92, 1.34) or of expert validation (β = 0.31,

Table 5. Cluster Characteristics in the Content > Context Contrast.

		Peak Voxel			Content > Context	
	#Voxels	**X**	**Y**	**Z**	**t(28)**	***p*-value**
L. Middle Frontal Gyrus	1093	-38	8	59	10.5973	<.001
L. Middle Temporal Gyrus (anterior)	326	-53	-50	-11	8.3608	<.001
L. Angular Gyrus	215	-35	-65	38	7.0977	<.001
L. Middle Temporal Gyrus (posterior)	142	-53	-74	8	-6.6132	<.001
L. Lingual Gyrus	128	-23	-98	-11	7.3491	<.001

Notes: As an indication of the size of the effect within each significant cluster, we provide t-test statistics, which reflect the mean activation difference between conditions collapsed across all voxels in the cluster.

95% CI = 0.11, 0.52). As noted above, a solution with high code quality was 11.69 times more likely to receive a higher final rating than one with low code quality, controlling for both expert and community validation. In the presence of code quality, both community and expert validation exerted a weaker effect on the final ratings, with odds ratios of 3.10 and 1.36, respectively.

To measure how neural activation patterns differ when evaluating contextual versus content information, we contrasted neural activation in the context phase with activation in the content phase. This analysis revealed a large cluster of significant activation encompassing much of the motor and visual systems. This cluster was likely due to the differences in the visual stimulus size and motor responses between the two phases of each block (i.e., participants made more button presses when responding to the content phase of the experiment) and thus is not discussed further here. Outside the visual and motor systems, we observed significant activation differences in five clusters, including the left middle frontal gyrus, left angular gyrus, two distinct regions in left middle temporal gyrus, and the left lingual gyrus (Table 5 and Appendix F). Activation was greater for the content phase in each of these clusters except the more posterior cluster in the middle temporal gyrus, which was more active during the context phase.

Influence of Congruent Versus Incongruent Cues

> *Question 5: Do cues exert an interactive effect on information filtering decisions when they are congruent versus when they are incongruent? What neural mechanisms are involved in processing congruent versus incongruent cues?*

To test the effect of cue congruence, we explored two scenarios: (1) when contextual cues are congruent or incongruent with each other, and (2) when contextual cues are congruent or incongruent with content quality.

First, do congruent contextual cues exert an interactive effect on filtering behaviors over and above the effects of the individual cues themselves? Considering the nonsignificant interaction term of EV × CV in model 1.2 ($\beta = .39$, $p = .106$), our results are unable to provide conclusive support for this notion. However, Figure 1 shows an interesting pattern (discussed later) in the probability plots derived from the cumulative odds for each level of expert and community validation.

To test for a congruence effect of contextual cues and content quality, we included two- and three-way interaction terms between the predictor variables in model 2.2. Results show that although none of the two-way interactions between the predictor variables is significant, the three-way interaction between expert validation, community validation, and code quality is significant ($\beta = 1.01$, $p < .05$). Figure 2 shows a simple-slopes diagram that represents the interaction between these three variables, with the dependent variable on the vertical axes representing the log odds (left side) and probability (right side) of a solution receiving the next-highest rating on the five-point scale. As shown in this figure, holding expert validation and community validation constant, low-quality solutions have an overall lower probability of receiving a higher rating than high-quality solutions. However, the contextual cues exert different effects at different levels of code quality. When community validation is high, it interacts more strongly with expert validation when code quality is also high. In other words, high expert validation magnifies the effect of high community validation when solutions are perceived as being high quality. The opposite appears to be true when community validation is low. In this case, low expert validation seems to cause judgments of solution quality to drop more precipitously when code quality is also low. Figure 3 shows the probability plot for this set of models.

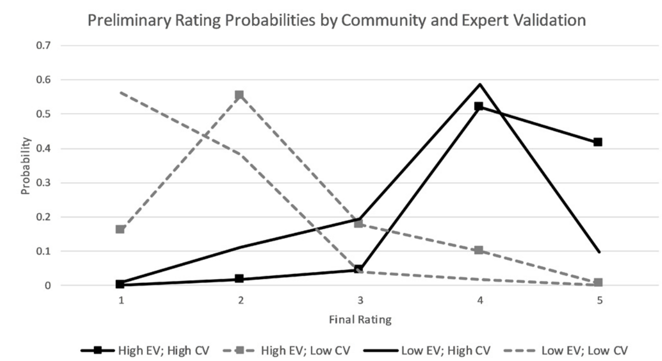

Figure 1. Probability of Rating Solution Based on Contextual Cue Valence

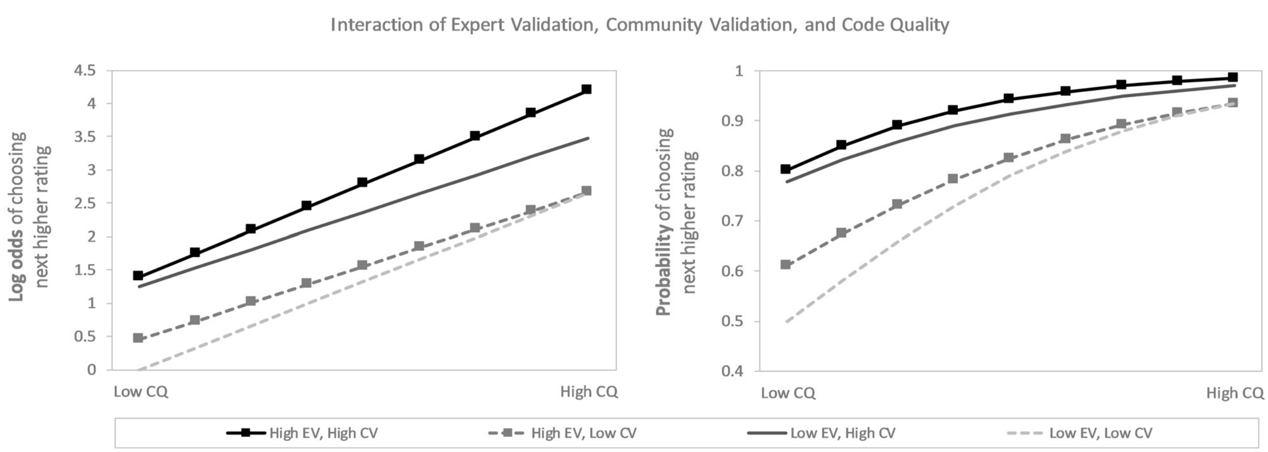

Figure 2. Interaction of Expert Validation, Community Validation, and Code Quality

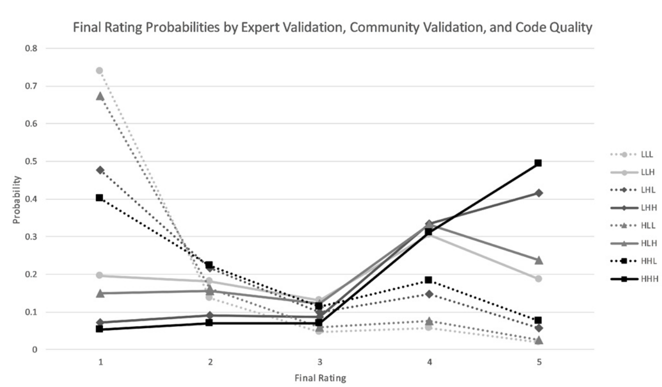

Figure 3. Probability of Rating Solution Based on All Cues

Table 6. Cluster Characteristics for Congruent Versus Incongruent Contextual Cues

		Peak Voxel			Congruent vs. Incongruent Cues		
Region	**#Voxels**	**X**	**Y**	**Z**	**F(1,28)**	***p*-value**	**partial eta^2**
L. Inferior Frontal Gyrus	72	-47	47	-2	23.857	<.001	.46
L. Ventrolateral Prefrontal Cortex	60	-53	32	23	26.37	<.001	.485

Notes: F-statistics reflect the mean activation differences collapsed across all voxels in the cluster and are provided as an indication of the size of the effect within each significant cluster.

To explore the neurocognitive processing associated with congruent/incongruent cues, we again performed repeated-measures analyses using AFNI program 3dMVM, with participant as a random factor and the factorial combinations of expert and community validation levels (HH, HL, LH, and LL) as a fixed factor. The contrast of congruent and incongruent contextual cues (HH and LL versus HL and LH) revealed two significant clusters of activation, detailed in Table 6. Activation in two frontal regions (located in the left ventolateral prefrontal cortex [vlPFC] and left inferior frontal gyrus [IFG]) was significantly greater when CV and EV were incongruent than when they were congruent (see Appendix F).

Finally, we conducted another repeated measures analysis to compare neural activity in the content phase of each trial when the final rating was consistent with the contextual cues (CV and EV) compared to when it was inconsistent with one or more contextual cue. We did not observe any significant clusters of activation in this contrast.

Discussion and Theoretical Propositions

Prior studies have begun to explore how people evaluate and filter knowledge they receive via various forms of technology-mediated channels (Fadel et al. 2009; Sussman and Siegal 2003; Zhang and Watts 2008) and online forums in particular (Fadel et al. 2015; Meservy et al. 2014). However, despite the relative maturity of forums as a knowledge source, we have, to date, made relatively little progress in exploring the cognitive processes that underlie forum information filtering. The purpose of this study was to take an exploratory step toward better empirical understanding of this phenomenon, with the dual objectives of building our theoretical understanding of how online information is processed and developing practical insights that will guide the development of the platforms on which they are based. The results of our experiment offer several interesting insights that both strengthen and challenge our nascent theoretical understanding of forum information filtering in IS research. In this section, we discuss these insights with respect to each of our research questions, and we consider their implications for ongoing theoretical development. Consistent with our theory-building approach, we employ reverse inferential reasoning (Poldrack 2006) to arrive at testable research propositions that can guide ongoing research and theory development in this area. We note that these propositions, although supported by external theory and our experimental data, are speculative in nature and are intended as a starting point for future theorization in the IS domain.

Q1: Valence of Contextual Cues

With respect to Question 1, our results show that the valence of contextual cues influences forum information filtering decisions. Theory suggests that the role of contextual cues should be greatest when knowledge seekers lack the ability or motivation to analyze the information content (Petty and Cacioppo 1986; Petty et al. 2005). However, our results suggest that these cues exert an influence even for experienced knowledge seekers. Our experimental design intentionally differs from prior studies in that participants were asked to render an initial judgment on the solution after viewing only the contextual cues; thus, it might be argued that reliance on these cues was artificially induced. Nevertheless, because our participants were experienced programmers and knew they would be able to view the solution content before rendering a final judgment, it seems plausible that participants might disregard these cues entirely in favor of content-based evaluation. Instead, we observed that participants were more likely to select a solution when it had received positive validation, either by an expert or by the community. Although contrary to predictions of dual process theories, this result corresponds with some decision research showing that expert decision makers can be influenced by (even random) contextual cues presented in the decision-making context (Ariely et al. 2003; Northcraft and Neale 1987). Moreover, the effect of contextual cues observed here is supported by recent research on forum information filtering. For example, Meservy et al. (2014) showed that the ratings of forum solutions by knowledge seekers who were subject matter experts tended to correlate highly with the positive/negative indications of associated validation cues, even when the indications of these cues were inconsistent with the actual solution quality. Taken together, these points of evidence imply that, in contrast to other forms of technology-mediated information exchange mentioned earlier (Fadel et al. 2009; Sussman and Siegal 2003), contextual cues play an important role in forum information filtering even when knowledge seekers possess the ability to evaluate solution content. We propose:

> *P1: Information filtering decisions on online forums are influenced by the valence of contextual cues, even among experienced knowledge seekers. Positive valence is associated with greater likelihood of solution retention.*

With respect to neural activity, we did not observe any brain regions that differentiated between positive and negative valence contextual cues. Although we must exercise caution when interpreting a null result, it is worth noting that our operationalization of positive and negative valence is somewhat different than what is normally used in the cognitive neuroscience literature—namely, positive and negative emotion (e.g., Russell 2003). It may be that high or low expert or community validation levels themselves were not sufficiently emotion-laden to differentially engage emotional valence processing, and thus did not result in differential activation patterns in our study. Alternatively, our results could be viewed as consistent with the bipolarity hypothesis of valence, which suggests that positive and negative are processed on the same neural dimensions (Barrett and Russell 1998). In short, contrary to our initial expectations, we failed to find evidence for distinct neural substrates responsible for processing positive and negative contextual cues. We therefore postulate the following:

> *P2. In forum information filtering, the processing of positively and negatively valenced contextual cues is neurologically non-differentiated.*

Q2: Influence of Content Quality

Our analysis shows that, when knowledge seekers possess the ability and motivation to do so, evaluation of content as high or low quality is highly influential in forum filtering decisions (Petty and Cacioppo 1986; Petty et al. 2005). Experienced knowledge seekers are able use their existing mental framework as a sort of "conceptual scaffolding" that enables judgments about the viability of a proposed solution. For example, the aspiring chef may use basic food pairing principles to determine if a recommended recipe is likely to produce the desired result, whereas a programmer would apply understanding of basic data structures, design patterns, or algorithms to assess a proposed solution to a programming problem. The results of our experiment confirm that for experienced knowledge seekers, content-based evaluation can have a significant influence in forum information filtering, similar to that observed in other technology-mediated information seeking contexts such as knowledge repositories (Fadel et al. 2009), email (Sussman and Siegal 2003), and online communities (Zhang and Watts 2008). Importantly, however, for forum information filtering, this influence does not occur at the exclusion of contextual cues, which also appear to influence judgments of even experienced knowledge seekers.

> *P3: Content quality has a significant influence on forum filtering decisions (assuming motivation and ability to evaluate content).*

From a neurocognitive perspective, we observed activation differences between solutions receiving a high or low final rating—specifically, large clusters of activation in the bilateral anterior insula for high-quality solutions. The anterior insula, along with the dorsal anterior cingulate cortex (dACC), is a major hub in the salience network, a set of brain regions that are activated for attentional capture by stimuli that are behaviorally or biologically important (Menon 2011). The salience network is thought to integrate and mediate the interplay between emotional and executive control processes (Menon 2011). Consistent with our findings, this network has been shown to be involved in engaging central executive functions (such as attention and working memory) (Goulden et al. 2014; Menon and Uddin 2010), which are crucial for evaluating information as in the forum filtering task. Other evidence suggests that the anterior insula is involved in domain-specific task-level control and focal attention (Nelson et al. 2010). Ploran et al. (2007) found that activation of the anterior insula and dACC tracked with the accumulation of evidence in a perceptual recognition paradigm. Accumulator models of decision making posit that evidence accumulates over time, until finally reaching a threshold corresponding to a certain response (van Vugt et al. 2016). Using reverse inference of participants' mental processes from the activation data observed, we propose that such a process may have occurred during our experiment as participants evaluated potential solutions and eventually recognized those that were of high quality. Specifically, our results suggest that content-based evaluation of forum solutions could entail an evidence accrual process wherein knowledge seekers engage their executive and memory-based neural faculties to effectively "build a case" in support of the solution they are evaluating. Identification of errors in low-quality solutions would essentially short-circuit this process, potentially explaining why these regions were less active for low-quality solutions.

> *P4: Evaluating forum solution content as high quality involves neural functions associated with accumulation of evidence and executive functions such as attention and working memory.*

Q3: Relative Influence of Expert- and Community-Based Contextual Cues

Many studies of technology-mediated information processing have examined only one contextual cue, typically source credibility (Sussman and Siegal 2003; Zhang and Watts 2008). In this study, we extend the boundaries of prior work by examining the understudied but important contextual cue of validation, and theorizing on the comparative influence of two types of validation—expert and community—on the filtering process. Our results show that community validation cues have a much larger influence on filtering decisions than do expert validation cues, a finding that corroborates literature in other domains (Dellarocas et al. 2007; Zhang et al. 2010). This finding points to a number of interesting possibilities for further theoretical development in this area, including exploration of how and why social, community-based cues are more influential. For example, social identity theory suggests that people tend to place more trust in others with whom they identify as being part of a homogeneous group than those perceived to be outside the group (Nesje 2009; Tanis and Postmes 2005). This perspective could potentially explain the elevated influence of community-based cues that originate from fellow knowledge seekers (e.g., "someone like me") over those that originate from more removed experts. This leads us to the following proposition:

> *P5: Community-based cues are more influential in forum information filtering decisions than expert-based cues, possibly due to social identification of forum knowledge seekers with other network participants.*

From a neural perspective, we did not find any significant activation differences for expert and community validation, possibly indicating a common neural index of the social cognition associated with validation cues originating from expert and community sources. This is at least partially consistent with other literature that has examined the neural pathways of social influence. For example, Mason et al. (2009) conducted an experiment in which participants evaluated symbols that they were told had been evaluated by a community (defined as "hundreds of people") as either preferred or not preferred. Consistent with other studies on the neuropsychology of social influence (Amodio and Frith 2006; Gallagher and Frith 2003; Mason and Macrae 2008), their results showed that the mere presence of the social rating was associated with greater activation in the medial prefrontal cortex, suggesting a possible neural index for a normative channel of social influence in general (Deutsch and Gerard 1955). However, our result contrasts with other research, which has shown different neural activation patterns associated with expert- and community-based cues. For example, Seiler and Walden (2016) conducted an experiment in which participants decided whether to strategically default on a mortgage loan based on either the decision of a real-estate expert, decisions of their homeowner peers, or no decision information. Similar to other research, they found that certain brain areas (e.g., the occipital pole, the lateral occipital complex, and the occipital fusiform gyrus) were generally more active in the presence of either expert- or community-based recommendations. However, they also found that decisions associated with expert opinions involved greater activations in the left inferior parietal lobe, whereas decisions associated with peer opinions were associated with right inferior parietal lobe and the right visual cortex, a difference they ascribe to informational herding versus social herding, respectively. One important distinction between these studies is that our experiment involved rating solutions that were objectively high or low quality, whereas Seiler and Walden asked participants to make mortgage default decisions that had no normatively correct answer. The results we observed imply that in normative information filtering scenarios, the distinction between social and informational channels of influence may be diminished proportionally to the participant's ability to evaluate the solution for themselves and arrive at the objective "right answer." In short, we propose that:

> *P6: In normative information filtering tasks, the neural processing of expert- and community-based contextual cues are handled by common neural systems responsible for processing social influence.*

Q4: Relative Influence of Content and Contextual Cues

Our results offer insights into the relative influence of content- and context-based processing that both confirms and contrasts with prior work. Past research on technology-mediated information seeking has pointed to a more prominent role for content-based processing in some domains (Fadel et al. 2009; Sussman and Siegal 2003; Zhang and Watts 2008) and contextual processing in others, including network forums (Fadel et al. 2015; Meservy et al. 2014). These studies reached their conclusions by allowing for simultaneous occurrence of both types of processing and then deriving the relative importance of these channels through *post hoc* participant reports or *in situ* observational data from an eye tracking device. Although this approach is certainly valuable for observing unconstrained information processing patterns, our experimental design in this study offers a unique perspective by employing a methodology that explicitly induces each type of processing separately. Our results for model 2.1 show that when participants consume content-based cues, they exert a larger influence on filtering decisions than does either of the context-based cues we studied (although contextual cues still remain influential). This implies that experienced knowledge seekers may reference contextual cues to *identify* solutions worthy of further consideration, but still rely on an evaluation of the solution content to determine whether to *adopt* the solution. For theoretical development, this suggests that although contextual cues have been repeatedly shown to influence filtering decisions of even experienced knowledge seekers, content-based processing remains the primary mechanism whereby solutions are ultimately adopted.

> *P7: When knowledge seekers possess adequate motivation and ability, evaluation of solution content has a greater influence on forum solution adoption decisions than does evaluation of contextual cues.*

Our fMRI analysis for Question 4 reveals robust effects for content- versus context-based processing. For the former, we found activation of the left middle frontal gyrus, left angular gyrus, and left anterior middle temporal gyrus. These regions are generally associated with the semantic processing network, which governs encoding and understanding of meaning associated with words and objects (Price 2010; Wagner et al. 2001). For context-based processing, we found that the left posterior middle temporal gyrus (pMTG) was significantly activated. The pMTG has also been implicated in semantic processing, although it is thought to fulfill a more regulatory function involving selective information retrieval and integration of simple automatic semantic processing with goal-oriented cognition (Davey et al. 2016). These results suggest at least two qualitatively different neurological mechanisms underlying forum information filtering: one involving effortful semantic encoding of solution content and one involving more automatic judgments based on contextual cues. Such an account is consistent with predictions of dual-process theories of cognition (Eagly and Chaiken 1984; Petty and Cacioppo 1986), which posit a central (systematic) route in which the semantics of the information are carefully evaluated, and a peripheral (heuristic) processing route in which quicker judgments are achieved based on application of rules associated with contextual elements. Forum contextual cues are self-evident and straightforward; the information they convey (i.e., positive or negative valence) can be consumed in fractions of a second, thus requiring a shallower level of cognitive processing. Evaluating solution content, on the other hand, requires the knowledge seeker to more deeply assess the semantics of the solution, carefully evaluating it against a mental representation of the solution domain to ascertain its quality. Both quantitative and qualitative differences in neural activation patterns have been associated with deep versus shallow encoding (Galli 2014); regions such as the left middle frontal, left middle temporal, and left angular gyri have commonly been associated with deeper semantic and language-based processing that might feature more prominently in content-based filtering (Price 2010; Wagner et al. 2001). Our results offer additional evidence that distinct types of neurological activity are indeed associated with the processing of certain forum elements, lending credence to the utility of dual process theories of cognition in explaining forum information filtering behaviors.

> *P8a: Content-based evaluation of forum solutions invokes neural systems associated with deep semantic processing.*

> *P8b: Context-based evaluation of forum solutions invokes neural systems associated with selective information retrieval and automatic semantic processing.*

Q5: Interaction of Congruent Versus Incongruent Cues

Our final question explored how filtering judgments are influenced by the combined (interaction) effects of both contextual cues and content. First, with respect to contextual cues alone, one might expect that the combined interactive effects of multiple cues would be greater than either cue individually. Although the results of our ordinal regression analyses do not allow us to infer statistical generalization for this idea, it is interesting to note the pattern of results observed for our particular sample, as shown in Figure 1. It is apparent from this figure that solutions with low expert and community validation levels (LL solutions) had the greatest probability of receiving the lowest rating of 1, whereas solutions with high levels on both context cues (HH solutions) had the highest likelihood of receiving the highest rating of 5. This can also be extended to the two lowest and two highest validation levels: LL solutions had a cumulative probability of 94.3% of receiving a rating of 1 or 2 (next highest was HL at 71.6%), whereas the probability of HH solutions receiving a rating of 4 or 5 was 93.5% (next highest was LH at 68.4%). One interesting pattern from this figure is that the probabilities of the two high-community-validation conditions and the two low-community-validation conditions are roughly parallel to each other (suggesting no interaction with expert validation), except at the endpoints of the rating scale. The diverging probabilities between LL and HL at the low end, and HH and LH at the high end, suggest that context cues may exhibit some interactive influence for solutions judged to fall at either of these extremes, although the effect may be tempered in the mid-range. One interesting theoretical possibility is that decision makers might initially anchor to the indication of one of the context cues (e.g., community validation) to decide on an initial rating, then adjust the anchor up or down depending on the values of the other context cue(s) available.

> *P9: The interactive effect of multiple contextual cues on filtering judgments is most pronounced when solutions are judged to be of very high or very low quality.*

When community and expert validation levels were in conflict, there was a network of brain regions that was differentially active, notably, the left vlPFC and IFG. Inferring from previous research, the situation where expert and community validation levels differ, or are incongruent, can be viewed as a form of prediction error where participants expect one outcome and become surprised when there is a conflict. Previous studies on prediction error using reward paradigms have shown that the striatum, anterior cingulate cortex, and lateral prefrontal cortex are reliably activated in such paradigms (Garrison et al. 2013). Other studies have demonstrated that the lateral prefrontal cortex is reliably activated when a prediction error occurs (Corlett et al. 2004). Our results are consistent with these findings. The vlPFC has also been associated with response conflict where two different responses are elicited and in response inhibition (Ridderinkhof et al. 2004) and is part of the frontoparietal attention network (Petersen and Posner 2012). Thus, activation here could also reflect response inhibition or increased attention in the face of incongruent cues. For theory, our results show that disagreement between contextual cues does have a measurable effect on the filtering process of forum users, who seem to expend some cognitive effort considering (and perhaps attempting to resolve) the discrepancy.

> *P10: Evaluating incongruent contextual cues on a network forum activates neural systems associated with prediction error.*

Another interesting implication of our results is the interaction of contextual cues and content. Information processing research has long suggested that contextual and content-based processing do not operate in isolation but in tandem (Chaiken 1987; Eagly and Chaiken 1984). Our results confirm that filtering judgments for high- and low-quality solutions are not constant but are instead swayed by the indications of contextual cues, particularly for low-quality solutions (see Figures 2 and 3). This is consistent with prior information processing theory, which has shown that contextual cues can bias or attenuate later judgments based on information content (Chaiken and Maheswaran 1994). Importantly, our results suggest that contextual cues serve as an anchor to subsequent evaluation of solution content, which may lead knowledge seekers to ascribe more or less value to a solution than they otherwise would if relying on content-based evaluation alone. Anchoring and adjustment is a widely observed psychological phenomenon (Furnham and Boo 2011) and has been shown to operate even in contexts where experts make evaluation decisions within their domain of expertise (e.g., Northcraft and Neale 1987); however, it has not been a focus of research on technology-mediated information filtering. Our results suggest that how and under what conditions contextual cue anchoring affects information filtering judgments in online forums is an important question for future theoretical development.

> *P11: Content-based evaluation of forum solutions is influenced by the indications of contextual cues, which serve as an anchor to content-based judgments.*

From a neural perspective, we explored if there would be activation differences due to conflict between context- and content-based cues, possibly due to cognitive dissonance or expectation violation. Previous research has shown that the anterior cingulate cortex and the dorsolateral prefrontal cortex demonstrate activation differences in situations of cognitive dissonance (Izuma et al. 2010). However, we did not observe any differential activation in situations where participants' final ratings were congruent with the community and expert validations versus when they were incongruent. This is in contrast to the behavioral result that indicated that contextual cues did in fact influence participants' subjective ratings of the proposed solutions. One potential explanation for this could be that when forum users are experienced, content-based judgments are sufficiently strong so as to render any discrepancy with contextual cues of little concern. In other words, although contextual cues may serve to nudge content-based judgments in one direction or another, forum users do not appear to expend cognitive energy trying to resolve discrepancies. Instead, they simply make their filtering decisions based primarily on their evaluation of solution content regardless of what the contextual cues indicate.

> *P12: When solution content quality is incongruent with the indications of contextual cues, experienced forum users do not attempt to cognitively resolve the incongruence but instead make judgments based on evaluation of content.*

In summary, the neural results of our study offer several important theoretical contributions that align with proposed opportunities for NeuroIS research identified by Dimoka et al. (2011). First, this study is the first to link localized brain areas to information filtering tasks on network forums, identifying specific areas of neural activity that are associated with forum filtering and allowing for inference of the underlying cognitive mechanisms at work. Establishing these neural generators is a critical step toward deeper theoretical understanding of the cognitive processes that underlie technology-mediated information filtering tasks. Second, the fMRI protocol utilized in our experiment allows for more proximal observation of underlying mental processes that could not be assessed through more conventional methods such as participant self-reports, or even other previously employed physiological techniques such as eye tracking (Fadel et al. 2015; Meservy et al. 2014). Finally, our study offers a complementary viewpoint to other electronic networks of practice studies by both supplementing existing data sources with brain imaging data, and providing neuro-level insights that both support and challenge previous IS research. Our neural results, although novel in the IS literature, point to brain regions and underlying cognitive functions that are largely consistent with insights from broader neuroscience research. This reaffirms the complexity of information filtering cognition in network forums, and the need for ongoing theoretical refinement surrounding the nuances of information filtering in this context. The exploratory, question-based approach taken in this study, although still uncommon in IS research, offers a useful template for future neuro-research in areas where there is little guidance about the neurocorrelates of IS stimuli. Figure 4 presents a graphical theoretical model that summarizes the research propositions derived from our results.

Implications for Practice

For practitioners, this study highlights several practical implications related to the design, development, and support of network forums.

Confirming past research (Fadel et al. 2015; Meservy et al. 2014), this study highlights the importance of contextual cues in evaluating solutions in forums. Not only should contextual cues be included, they should be employed in a way that influences the ability of knowledge seekers to find and consider potential solutions. Interestingly, there are still many knowledge forums that lack useful contextual cues that can serve as a proxy for content quality.

We found support for the idea that the valence of contextual cues influences information filtering decisions of forum knowledge seekers. This finding underscores the importance of providing cues that can represent both positive and negative evaluations of the content presented. Forum owners and designers should consider contextual cues that convey both positive and negative information such as aggregate scores, percentages, and other valenced representations rather than only positive or negative indicators in isolation.

Perhaps the most significant practical implication from this study related to contextual cues is the influence of different types of validation. Previous research (Meservy et al. 2014) highlighted the importance of validation as a contextual cue and showed that it should be included in network forums. In this study, we extend this work by investigating the effects of two different types of validation: community and expert. Our results suggest that community validation is more influential than expert validation. Although some network forums restrict the validation of content to experts or moderators, we suggest that forums also provide mechanisms to allow the community to validate content.

Designers should also consider the relative accuracy of various contextual cues and highlight not only those that are most influential but also those that provide the most faithful representation of the underlying content. As such, forum designers need to consider which cues to display, how various contextual cues should be arranged, and how multiple solutions should be presented based on the relative strength of associated cues. In our observation, most forums present solutions in reverse chronological order, with more recent contributions listed first. Alternatively, forum designers could consider first presenting solutions containing certain combinations of contextual cues (e.g., solutions validated by an expert and highly rated by the community), but should exercise caution to avoid self-reinforcing biases.

Our results suggest that certain combinations of contextual cues are processed differently by the brain. Forum designers should be aware that conflicting cues invoke different cognitive processing patterns and may produce error-detection-related processing, which might lead to users focusing on the conflict and having lower confidence in the presented solutions.

We suggest that more designers incorporate contextual cues as explicit filtering criteria in the knowledge acquisition process. This recommendation not only applies to individual network forums but also extends to search engines that index multiple forums. In addition to providing keyword terms, the ability to search, sort, and filter by contextual cues would allow knowledge seekers to form and refine their consideration set by focusing on the most probable content. Although some search engines incorporate contextual cues related to

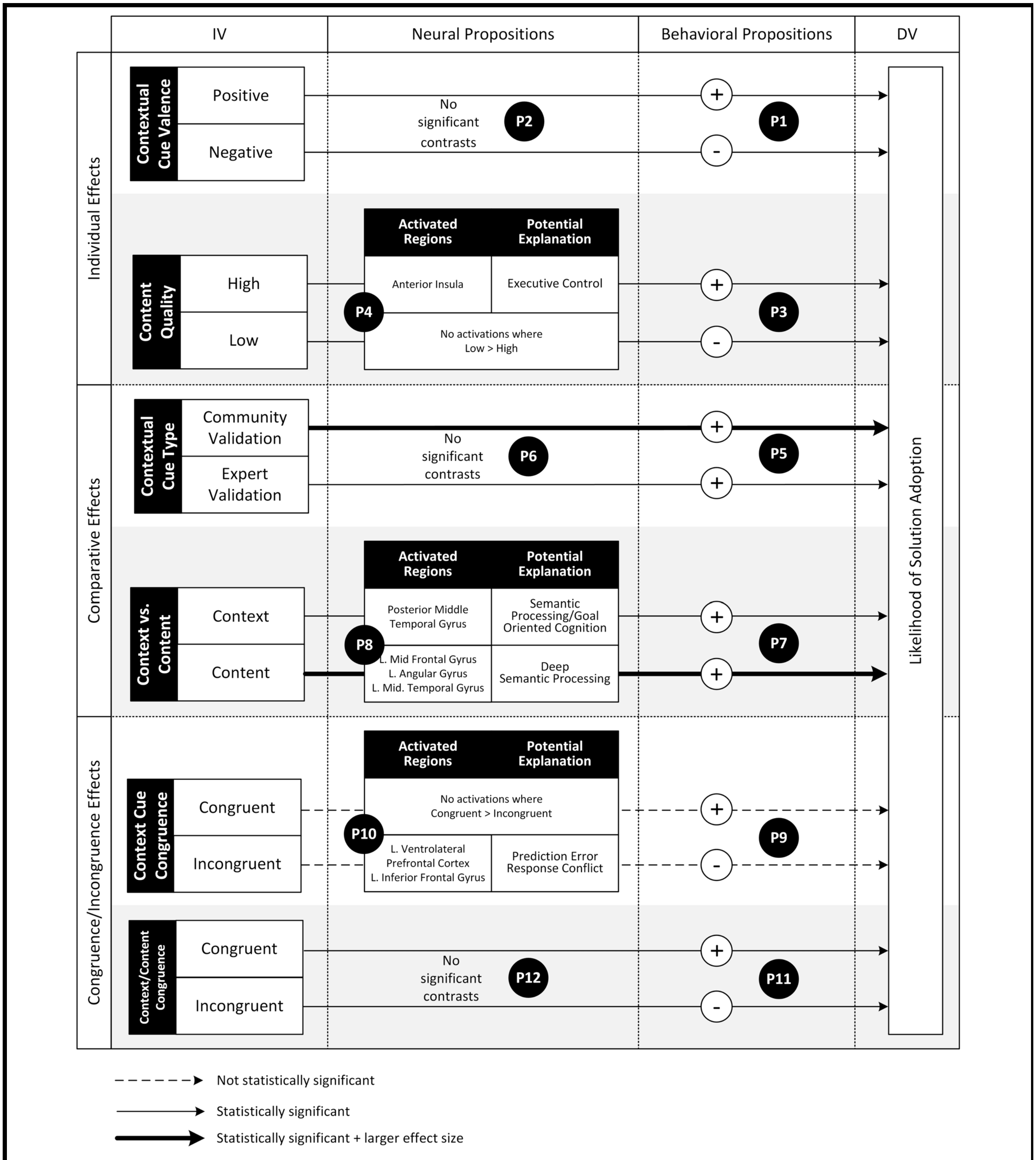

Figure 4. Theoretical Model and Research Propositions

product information (Litza 2016), to our knowledge few, if any, incorporate contextual cues related to information assets that are indexed by search engines. Additionally, we are unaware of any search engines that allow users to specify the relative importance of these cues during the search process.

Limitations and Future Research

This study has some limitations. First, as with any experimental research, external validity may be limited due to the controls and context of the experiment. We attempted to maximize internal and external validity by developing an experimental instrument that was based on actual online forums and content and by recruiting experienced software developers who use network forums to solve problems. Still, having participants evaluate forum solutions within an fMRI machine is unavoidably different than a similar task in a more natural setting. Unlike many fMRI studies that simply display stimulus materials in rapid succession, we developed an interactive instrument that allowed participants to engage in systematic processing of information. However, we intentionally separated contextual processing from content processing. Although this design was purposeful and yielded interesting results, all of these circumstances pose potential threats to external validity; therefore, additional research is needed to corroborate our findings and generalize them to a broader context.

Second, to preserve internal validity, contextual cues and associated information such as expert name and information, as well as avatars, were randomized to allow us to isolate the influence of different types of network forum information. Therefore, even though certain elements might introduce a bias (e.g., more complex cognitive processing associated with faces), the influence of these cues was randomized across participants and conditions. Further, in our experiment, the indications of the contextual cues had no correlation to the actual quality of the solutions. Even though participants were told in verbal and written instructions that each solution had been rated by an expert and by the community members, it is still possible that participants could have doubted the validity of the expert and community ratings.

Third, despite our efforts to attract a diverse population of programming professionals, our final sample was 93% male. Although this is reflective of the general skewed distribution of males in high tech industries (Murthy 2014), it may adversely affect the generalizability of our results.

Finally, although the use of fMRI technology allows us to observe cognitive processing by detecting blood oxygenation levels relative to a baseline or comparative condition, it does not offer a perfect reflection of actual cognition. Nevertheless, to our knowledge, this is one of the first studies to investigate cognitive processing associated with information filtering tasks on network forums. We encourage additional research using fMRI and other techniques to deepen our understanding of how information influences decision making online. Alternative neuroimaging techniques can provide enhanced temporal (e.g., EEG) and spatial (e.g., PET) resolution, which will add to our understanding of these phenomena.

Several additional opportunities exist for future work to build upon our findings and extend theoretical development in this area. For example, our study used one operationalization of contextual cues, but other ways of implementing these cues might alter their relative influence. Community votes, for instance, may take the form of raw vote counts or star ratings, while expert ratings may be operationalized in similarly diverse ways. Moreover, contextual cues can also be combined in different ways (i.e., solutions could be validated by experts who, in turn, are ratified by the community). A detailed exploration of the effects of different types of contextual cues and their combinations on forum information filtering decisions is uncharted territory in the IS literature, but constitutes a critical step for ongoing theoretical development in this area. Another interesting question concerns the circumstances under which contextual cues anchor content-based judgments and whether the sequence of exposure to different types of cues influences this anchoring effect. In short, our results and theoretical propositions reveal a plethora of interesting avenues for additional theoretical refinement surrounding how forum elements are operationalized and combined and how these configurations affect the information processing patterns of knowledge seekers.

Conclusion

In an era of unprecedented access to information, online forums sponsored by electronic networks of practice will continue to proliferate as a primary source of technology-mediated information exchange, necessitating deeper understanding among both scholars and practitioners of how such information is evaluated, filtered, and consumed. This study extends the nascent but growing body of literature in this area by offering a NeuroIS perspective on forum information filtering. We identify two types of contextual cues involved in network forums and confirm the importance of validation, especially community validation, in information filtering decisions. Moreover, utilizing fMRI data, our study provides direct empirical evidence of the diverse neurological processes involved in forum information filtering, showing how evaluation of various types of context- and content-based cues engages different neurocognitive mechanisms and leads to different filtering outcomes. We encourage future research that builds on the groundwork laid by this study to elucidate further the behavioral and neural underpinnings of forum information filtering.

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MIS Quarterly

RESEARCH ARTICLE

AN FMRI EXPLORATION OF INFORMATION PROCESSING IN ELECTRONIC NETWORKS OF PRACTICE

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Appendix A

Prior IS Research on Electronic Network of Practice Forums

Recent IS research has begun to explore behavioral filtering patterns associated with content and contextual cues on a network forum. Using eye-tracking technology, this work has shed light on the cues attended to during filtering (Meservy et al. 2014) and how the attentional switching patterns between these cues (e.g., evaluating all cues of a single solution versus comparing a single cue across multiple solutions) affects filtering accuracy (Fadel et al. 2015). In the present study, we extend this prior work while making note of two important observations. First, although these studies have shed light on the role of different types of cues in forum information filtering, they are limited with respect to their ability to elucidate the actual cognitive processes that underlie this filtering. Gaze data from an eye-tracker can prompt inferences about the types of information attended to during the filtering process, but it is silent on the neurocognitive processes that occur. This leaves several important questions for ongoing theory development. For example, are different types of cues (e.g., content versus contextual) processed by different cognitive centers in the brain, which, depending on their relative activation levels, could produce more or less accurate filtering decisions? Or do similar neural mechanisms underlie both content and context-based processing, and any difference lies only in the type of information evaluated? Moreover, which types of cues are most important when filtering solutions, and how do combinations of cues affect this filtering process on both a behavioral and a cognitive level?

Second, prior studies have relied on dual process theories of cognition (Chaiken 1987; Petty and Cacioppo 1986) as a theoretical frame for examining information filtering on a network forum. Originating in the domain of persuasion psychology, dual process theories posit that persuasion can occur via two primary cognitive routes: the central (systematic) route, in which the arguments of the message itself are carefully evaluated, and the peripheral (heuristic) route, in which judgments are made primarily based on surrounding peripheral cues (Chaiken 1980; Petty et al. 2005; Petty and Cacioppo 1986). Applying this framing to the context of solutions on a network forum, central route processing would entail evaluation of solution content, and peripheral route processing would rely on evaluation of surrounding contextual cues such as source expertise and validation (Fadel et al. 2015; Meservy et al. 2014). We believe this conceptualization offers a useful lens for characterizing different types of information filtering behaviors; however, dual process theorists have noted that cues themselves are not categorically central or peripheral, but instead can play a dualistic role, influencing judgments either centrally or peripherally depending on their context and relevance to the information content being evaluated (Chaiken and Trope 1999). As observed by Petty et al. (2005, p. 110), "certain variables have a chameleon quality in that they induce different processes in different situations. Therefore, any given variable should not be thought of as exclusively fulfilling any one role." In this paper, our objective is not to label specific cues as strictly central or peripheral per se, but rather to explore the cognitive differences between filtering based on these cues. We therefore employ the terms *content* and *context* to refer, respectively, to solution content and surrounding contextual cues such as expert and community validation.

Appendix B

Experimental Instrument

Table B1. Problem Descriptions

Phase	Problem	Description
Training	Split a string on spaces	Write a block of code that splits a string into separate strings everywhere there is a space.
Experiment	Concatenate two lists	Write a block of code that takes two lists or arrays of integers and concatenates them together into a single new list or array.
Experiment	Calculate the factorial of a number	Write a block of code that calculates the factorial of an integer (the product of the integer and all the integers below it).
Experiment	Identify the greatest element in an array	Write a block of code that determines the largest value in an array of integers.
Experiment	Sum the values of an array	Write a block of code that computes the sum of all the values in an integer array.
Experiment	Split array	Write a block of code that splits an array of integers into two separate arrays or lists at a predetermined point.
Experiment	Check for palindrome	Write a block of code that determines whether a string is a palindrome (a word is spelled the same forward or backward).

Eight solutions for each problem written in C#, Java, or C++ were gathered from programming forums, standardized to C#, and validated for use in the experiment. These languages were selected because they are syntactically similar to each other and are among the most popular modern programming languages (Cass 2016; TIOBE 2016). The figures below show examples of these solutions in the experimental instrument.

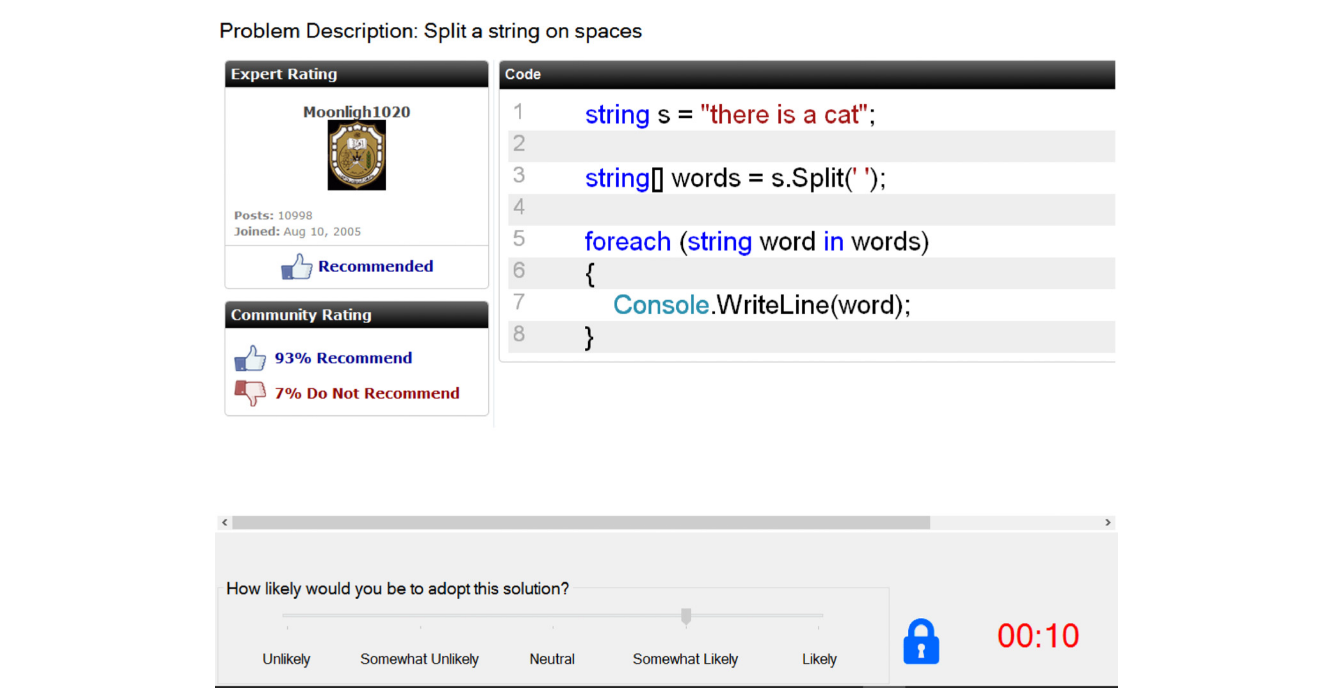


Figure B1. Sample Stimulus

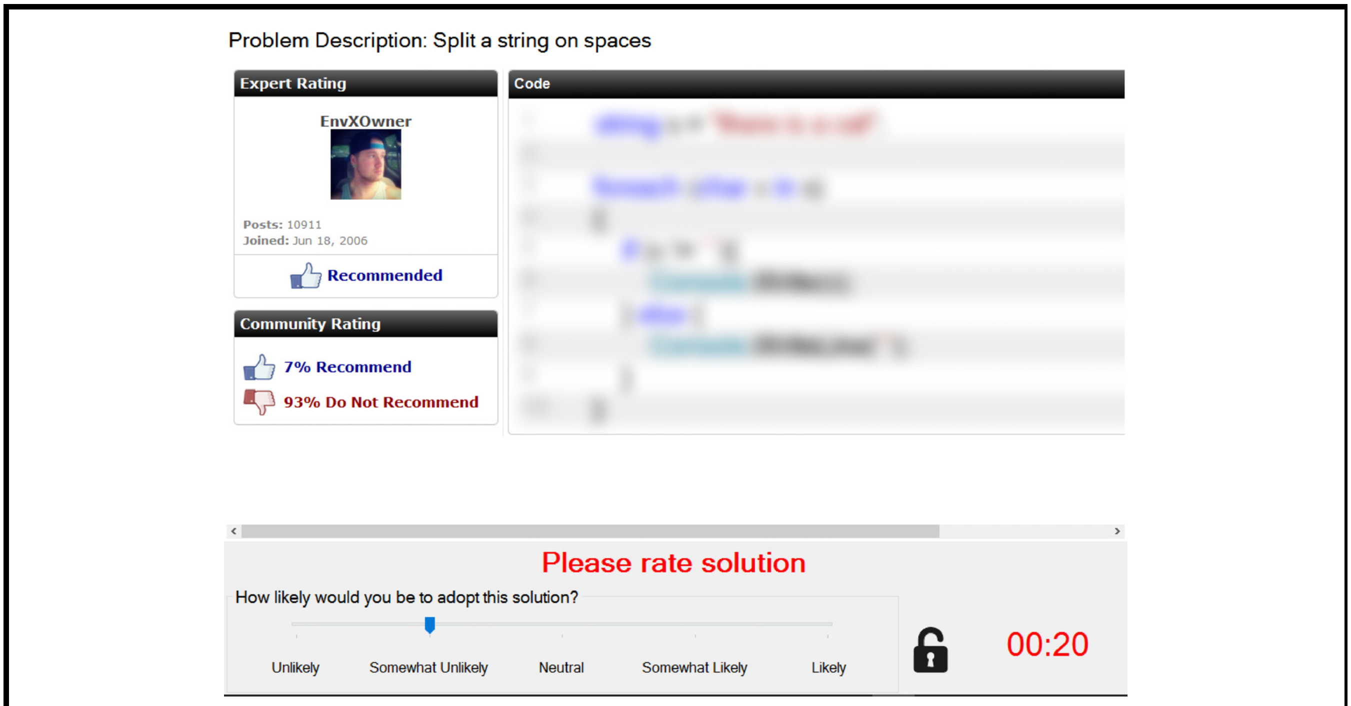


Figure B2. Sample Blurred Stimulus (Context Phase)

Appendix C

Experimental Procedure

A high-level overview of the experimental procedure is shown in Figure C1. When participants arrived at the MRI facility, they were presented with a consent form and again completed an MRI screening form to ensure their safety inside the scanner. Participants were then shown an introductory video to acclimate them to the scanner and to explain the experimental instrument and associated task. The video explained that each participant would be shown solutions to several programming problems and would be asked to rate each solution using a hand-held controller that operated the custom experimental instrument while in the scanner. After the video, the researchers answered any questions related to the task, the experimental instrument, the programming solutions, or any safety concerns associated with the scanner.

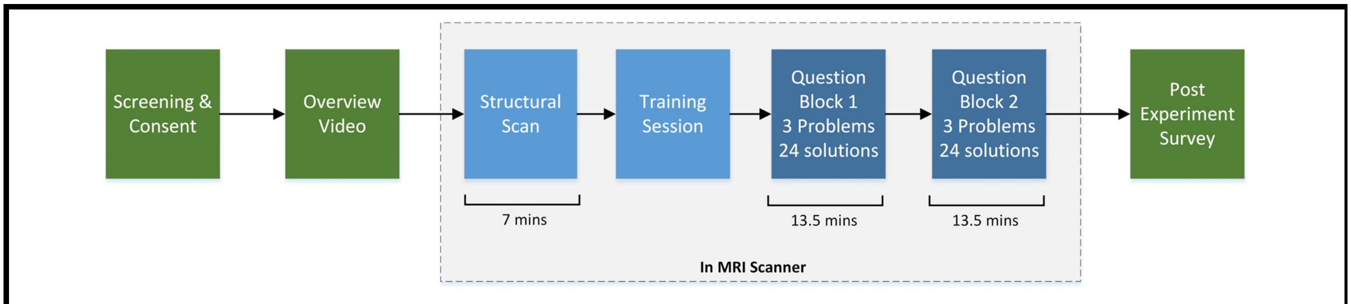


Figure C1. High-Level Overview of Experiment

After the introductory/consent process, each participant was taken to the scanner room and prepared for the experiment. The participant was first outfitted with headphones and a microphone to enable periodic communication with the researchers during the experiment. This ensured the participant's safety and ongoing comprehension of what s/he was asked to do. The participant was then situated in the scanner, and an initial standard-resolution localization and structural scan (approximately 7 minutes) was conducted to capture the participant's brain structure so that it could be co-registered with the functional MRI data. Following the structural scan, a training run was conducted to familiarize the participant with the experimental instrument. In this run, the participant was presented with four different solutions to a single programming problem. Each solution was presented for a total of 30 seconds, comprising both the context and content phases described above. Between each presented solution, there was a short,two-second break during which the participant was shown a baseline block (a gray screen with a black cross in the middle), as is common in fMRI experiments (Huettel et al. 2003; Jenkins et al. 2016). At the conclusion of the training run, researchers answered any remaining participant questions before proceeding to the experimental task. Figure C2 shows the timings for each block presented.

During the primary experimental task (27 minutes), the participant was shown each of the 48 programming solutions in sequence. Participants viewed the experimental stimuli on a large MR-compatible monitor at the opening of the MRI scanner by means of a mirror attached to the head coil. The participant used a four-button handheld controller to interact with the instrument and provide ratings of the likelihood of adopting the presented solutions. Each solution was presented for a total of 30 seconds, comprising both the context and content phase described above, followed by a two-second break during which the participant was shown the baseline block. As each context and content phase was self-terminated when the participant locked in a rating (see Figure C2), each of these events had a variable duration. Consequently, in our fMRI individual-level (first-level) regression analyses described below, we modeled the context phase and content phase as variable-length events. The time remaining in each 30-second block after participants had locked in their content rating was included with the 2-second inter-trial interval in the model's baseline, thus accomplishing a random temporal jitter between trials in the model. This represents a mixed blocked/event-related design (Petersen and Dubis 2012) where the task occurred in extended periods (as in a block design) but were of a variable duration and had a variable delay between them (as in an event-related design). This design more closely mimics what a participant might do when seeking information from an online forum.

To minimize cognitive burden and participant fatigue, solutions were grouped by problem, and the six problems were randomly grouped into two 3-problem blocks so that the participant could rest between blocks. To avoid any confounding effects due to ordering, all other aspects of stimulus presentation were randomized, including problem order, solution order within each problem, expert and community validation levels, and information about the expert who validated the solution. After concluding the primary experimental task, the participants were escorted out of the scanner to an adjoining room, where they completed a short survey that captured demographic information and perceptions about the experimental task.

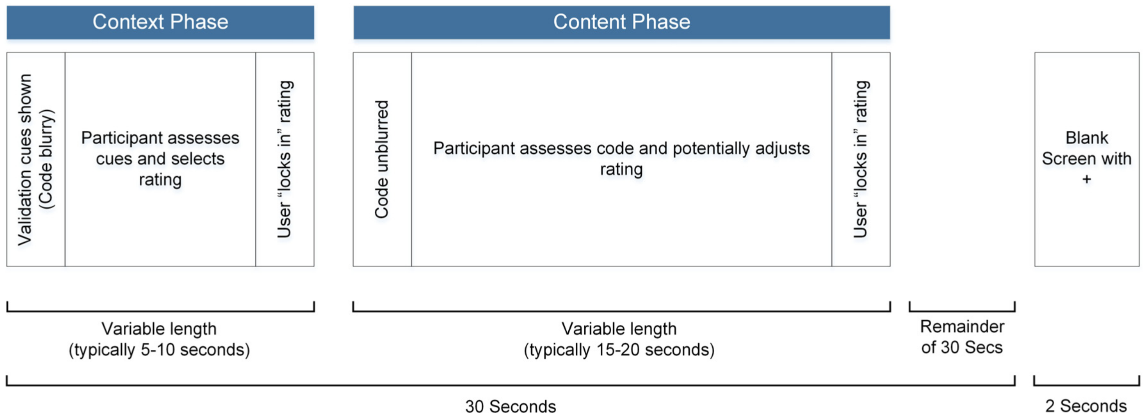


Figure C2. Overview of Each Block

Appendix D

Ordinal Mixed Effects Regression Models Suitability

Before employing ordinal mixed effects regression models with both fixed and random effects, we estimated a series of preliminary models to determine whether multilevel analysis was appropriate for our data (i.e., whether the higher-order variables of solution, problem, and participant exerted discernable random effects on the dependent variable). We began by estimating a single intercept-only baseline model with final rating as the dependent variable. We then estimated a random-effects-only model with final rating as the dependent variable and random intercept effects for solution, problem, and participant. A log likelihood comparison test revealed that the fit of the random-effects-only model improved significantly over that of the baseline (χ^2 = 434.32, p < .001), indicating some explanatory power of the grouping variables. To ascertain the magnitude of the individual random effects, we calculated an intraclass correlation (ICC) for each higher-order variable (Snijders and Bosker 2012), which indicates the proportion of total variance in the final rating explained by each higher-order variable. Solution had the largest ICC (.34), followed by participant (.04) and problem (.00). We tested the significance of these effects by comparing the fit of models that included each random effect independently against the fit of the baseline model. Results showed no significant improvement in fit for problem, indicating that the problems into which the solutions were grouped did not affect the final ratings. Effects for both solution (χ^2 = 404.11, p < .001) and participant (χ^2 = 13.989, p < .001) were significant, indicating that average final rating did vary somewhat by both participant and solution. However, although participant effects were entirely random in our design, solutions were experimentally manipulated by altering their code quality, which could account for at least some of the between-solution variance in final ratings. We therefore estimated an additional mixed-effects model that included code quality as a fixed-effect covariate. As expected, the ICC of solution (.09) dropped substantially under this model; however, a log likelihood comparison still showed a significant random effect for solution (χ^2 = 56.741, p < .001), indicating that final ratings may have been higher (or lower) for some solutions than for others due to experimentally exogenous factors. Therefore, although the ICC values indicate relatively modest random effect sizes, we retained both participant and solution as higher-order random effects variables in our analyses to account for their potential explained variance in the solution ratings.

Appendix E

fMRI Analysis

Two individual-level regression analyses were conducted to fit the ideal hemodynamic response to the brain data. Both used six motion regressors (for roll, pitch, yaw, and translations in the X, Y, and Z directions) and seven polynomial regressors per run to account for scanner drift in addition to behavioral regressors coding for task conditions. All behavioral regressors were modeled as a boxcar function with variable duration according to the participants' latency to respond convolved with the canonical hemodynamic response.

The first regression analysis separately modeled the four factorial combinations of high/low community and high/low expert validation levels in the context phase of each trial in order to test the effect of context cues on the preliminary ratings in the context phase. To test the effect of the consistency between context cues and final subjective rating, the regression model also contained two regressors coding for whether the final subjective rating of the solution was consistent with both the expert and community validation (i.e., all high levels or all low levels). Two more regressors coded for final ratings that were high or low but where the expert and community validation levels were mixed (one high and the other low).

The second regression analysis modeled four regressors according to whether the subjective participant rating was high or low in either the context phase (preliminary rating) or the content phase (final rating), regardless of the community or expert validation or the objective code quality. These models, which were used to test processing in the content phase, were included under the rationale that participants' neural activation patterns would correspond more closely with their perceptions of the information being presented (i.e., a solution believed by the participant to be high quality) than with the actual treatment condition.[1] For these models, subjective ratings of 4 or 5 were collapsed as "high" and ratings of 1 or 2 were collapsed as "low."

Structural data were first co-registered to the functional scans and then normalized to MNI template space using ANTs. The results of the single-subject regression analyses (known as beta maps or parameter estimates) were blurred using an 8mm FWHM Gaussian and then normalized to MNI space using the transformation calculated from the structural scan alignment. All group-level analyses described below were performed in MNI space and were masked for regions where we had spatial coverage in the functional scan for all participants in the sample, resulting in the exclusion of the more inferior aspect of the cerebellum since coverage of the cortex was prioritized.

We corrected for multiple comparisons using the AFNI 3dClustSim program, which uses Monte Carlo simulations to calculate the appropriate clusters of voxels that are large enough to be statistically significant (Forman et al. 1995; Xiong et al. 1995). Spatial smoothness was estimated for each subject using AFNI program 3dFWHMx based on the residuals resulting from the individual-level regression analyses described above (see Cox et al. 2017). The mean smoothness parameters for the group were used in the 3dClustSim program as the estimate of overall spatial smoothness when simulating the noise distribution. Based on the Monte Carlo simulations, we used a voxel-wise threshold $p < .001$ and minimum cluster threshold of 58 voxels.

[1]As noted in the paper, a Pearson chi-squared test of independence showed that final ratings were closely associated with the high and low experimental conditions for expert rating ($\chi^2 = 166.48$, $p < 0.001$) and community rating ($\chi^2 = 886.66$, $p < 0.001$) in the context phase and code quality ($\chi^2 = 401.52$, $p < 0.001$) in the content phase.

Appendix F

fMRI Results

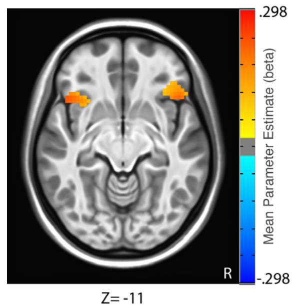
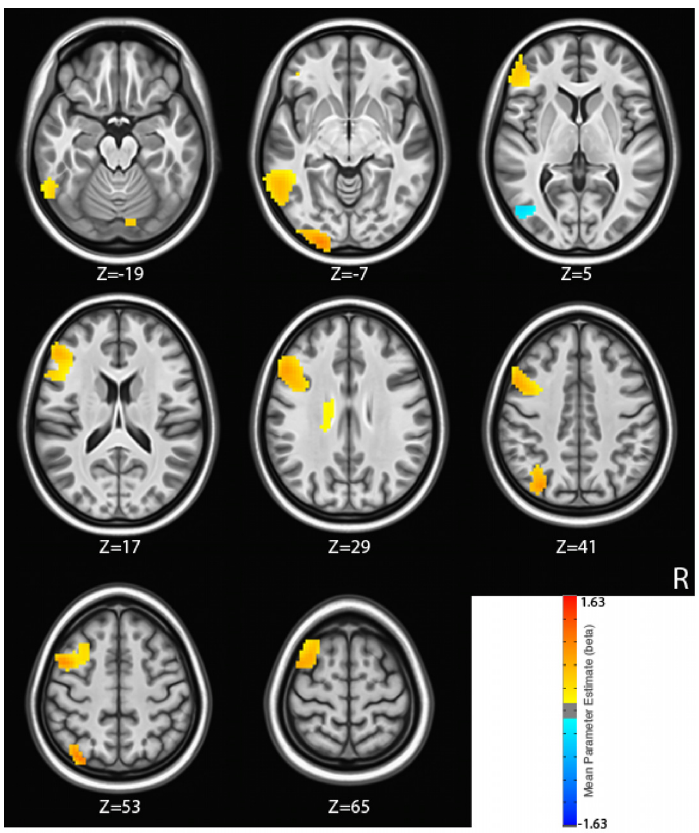


Figure F1. Clusters of Significant Activation in the Contrast of High Final Rating > Low Final Rating Included in the Bilateral Anterior Insula. R = right



As this contrast resulted in large activation differences, all results are presented with voxel-wise $p < .0001$ and a spatial extent threshold of k > 58 contiguous voxels.

Figure F2. Clusters of Significant Activation in the Contrast of Content Phase > Context Phase. R = right

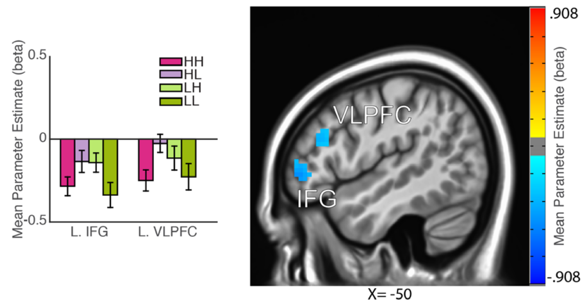


Figure F3. Clusters of Significant Activation for Congruent (Top) Versus Incongruent (Bottom) Contextual Cues

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