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RESEARCH ARTICLE

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Information Filtering in Electronic Networks of Practice: An fMRI Investigation of Expectation (Dis)confirmation

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Abstract

Online forums sponsored by electronic networks of practice (ENPs) have become an important platform for technology-mediated knowledge exchange, yet relatively little is known about how ENP participants filter and evaluate the information they encounter on these forums. This study integrates perspectives from expectation confirmation theory, prospect theory, and neuroscience research to explore how ENP forum filtering judgments are influenced when expectations formed on the basis of contextual cues are confirmed or disconfirmed by the examination of solution quality. We summarize six different models of expectation confirmation explored in previous IS literature and report the results of a neuroimaging experiment using functional MRI (fMRI) that paired both positive and negative contextual cues with high- and low-quality solutions on a mock ENP forum interface. Results show that evaluation judgments are strongest in conditions where initial contextual cue judgments are confirmed by examination of solution quality except when the perceived expectation-experience gap is large, providing evidence for an assimilation-contrast model of expectation confirmation. We also found neural activation differences for expectation confirmation vs. disconfirmation and, consistent with prospect theory, differences in filtering behaviors with respect to unexpected gains vs. unexpected losses.

Keywords: Electronic Networks of Practice, Expectation Confirmation Theory, Prospect Theory, NeuroIS, fMRI

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1 Introduction

Electronic networks of practice (ENPs) are groups of loosely connected, geographically separated individuals who share common interests and communicate over technology-mediated channels (Wasko et al., 2004, 2009; Wasko & Faraj, 2005). In today's era of online communication, ENPs have become an important and popular medium for knowledge exchange because of their open nature and the diversity of domains they cover, ranging from parenting (www.parenting.com/parenting-forums), paragliding (www.paraglidingforum.com), and programming (www.stackoverflow.com), just to name a few. Although ENPs may comprise hundreds or thousands of participants, exchanges that take place on ENP forums are typically dyadic: an individual seeking a solution to a problem posts a question to which other network participants can respond (Beck et al., 2014). Because of their open nature, a single query posted to an ENP forum may elicit several responses from a variety of ENP participants, ranging from highly specialized subject matter experts to casual observers. Thus, an ENP knowledge seeker faces the challenge of evaluating multiple responses to a query and evaluating which is best suited to solve the problem at hand, a process termed *information filtering* (Fadel et al., 2015; Meservy et al., 2014). To aid in this filtering process, most forums offer *contextual cues* surrounding each solution that offer indications as to its purported quality. These cues may include indicators of the expertise of the solution author, endorsement of a subject matter expert, or an aggregation of community feedback about a given solution. Such cues can help to quickly eliminate or target specific solutions in the filtering process; however, there is no guarantee that the indications of these cues will be consistent with each other or accurately reflect the true quality of the solution. The ENP knowledge seeker must therefore engage in a filtering process that relies on (1) evaluation of contextual cues, (2) evaluation of the solution content itself, or (3) some combination of both.

One particularly salient characteristic of ENP forums is that, unlike other technology-mediated knowledge exchange platforms such as email (Sussman & Siegal, 2003) or knowledge repositories (Fadel et al., 2009), the multiplicity of solutions and cues available on ENP forums present a complex information filtering task where consistent or conflicting signals may exist about the utility of a given solution. For example, an ENP knowledge seeker may form expectations about the utility of a posted solution based on its surrounding contextual cues (e.g., an endorsement by an expert or the community), only to find that these expectations are violated when examining the content of the solution. Alternatively, the knowledge seeker may anchor on the indications of certain cues and then fail to adjust filtering judgments in light of subsequent contradictory evidence. In such a scenario, it is not clear how different combinations of cues influence both each other and ultimate filtering judgments. Exploring both the behaviors and cognitions involved in this type of multi-attribute, multi-alternative filtering task constitutes an important step toward better theory development surrounding the use of ENPs as a mechanism for technology-mediated knowledge exchange.

In this paper, we examine how ENP information filtering judgments are influenced, both behaviorally and neurocognitively, by different combinations of contextual cues and solution content. Drawing from expectation confirmation theory (Oliver, 1980, 2010) and neurological studies of prediction error (Schultz, 2016; Schultz & Dickinson, 2000), the central premise of our theorization is that initial *expectations* about a solution based on contextual cues can be *confirmed* or *disconfirmed* by evaluation of the solution content, and that this confirmation/disconfirmation has differential effects on both filtering outcomes and cognitive processes that underlie the filtering process. Based on prospect theory (Kahneman & Tversky, 1979), we further postulate that the nature and magnitude of these effects will differ depending on their *directionality*; i.e., when expectations are positively disconfirmed (exceeded) vs. when they are negatively disconfirmed (unmet). We examine these postulates using a *NeuroIS* study design to better understand how ENP information filtering judgments are influenced by various combinations of contextual cues and solution content at both a behavioral and cognitive level. NeuroIS is a nascent branch of IS research that "relies on neuroscience and neurophysiological knowledge and tools to better understand the development, use, and impact of information and communication technologies" (Riedl et al., 2010, p. 245). A NeuroIS approach is particularly valuable for theory development surrounding ENP information filtering, as it sheds light not only on the *behaviors* associated with this filtering but also on the *neurocognitive structures and processes* that underlie these behaviors. We conducted a controlled fMRI experiment using a custom instrument that mimicked the structure of an ENP forum and measured participants' behavioral and hemodynamic responses to contextual cues and subsequent evaluation of solution content. We report both the behavioral and neural results of our experiment and theorize on the possible cognitive underpinnings of filtering in these scenarios.

The results of our experiment contribute to extant IS literature on both ENPs (Fadel et al., 2015; Meservy et al., 2014, 2019) and expectation confirmation (Brown et al., 2008, 2012, 2014) in two primary ways. First, from a behavioral perspective, we explore how expectations and experiences interact in ENP filtering tasks. In IS research, although expectation confirmation theory has been applied to the domain of information *technology* acceptance and continuance, to our knowledge it has not been applied to the way that *information itself* is filtered and evaluated; yet, just as people can form expectations about the utility of an information system, so too can they form expectations about the utility of information itself (Bozan & Berger, 2018; Delone & Mclean, 1992, 2003). Moreover, as evidenced by the divergent results of both IS and broader research, it seems probable that different theoretical models of expectation confirmation could offer more or less explanatory power depending on the context in question. In this study, we postulate a unique pattern of results based on each of six competing models of expectation confirmation and, based on experimental data, show that ENP filtering judgments conform most closely to an assimilation-contrast model. Consistent with prospect theory (Kahneman & Tversky, 1979), we also show a differential effect of gains and losses in information filtering; namely, that information judgments based on content assimilate more toward contextual cue indications when expectations based on these cues are negatively disconfirmed vs. positively disconfirmed. To our knowledge, this is the first study to explore how these expectations and experiences interact with respect to online information, thus constituting an important theoretical and empirical step toward better understanding of ENP filtering behaviors.

Second, this study employs a NeuroIS approach using functional MRI (fMRI) data collected during the experiment to examine the neural mechanisms associated with expectation (dis)confirmation in ENP information processing. Dimoka et al. (2011) identify seven possible ways that NeuroIS methods can contribute to the corpus of knowledge in IS; this study contributes to the IS literature in at least three of these ways. First, by testing for unique brain activation patterns when ENP knowledge seekers experience confirmation vs. disconfirmation, we *localize the neural correlates* of these constructs in the domain of ENP information filtering. Establishing these correlates is an important first step toward understanding common vs. differentiated cognitive processes involved in this context. Second, our study *complements existing data sources* with brain data that show what occurs on a neurocognitive level when expectations are confirmed vs. disconfirmed. Specifically, we show distinct activation patterns in regions associated with functions such as error detection and reward anticipation, including the anterior cingulate cortex (ACC) and anterior insula when people experience disconfirmation vs. confirmation, and the ventral striatum in connection with positive and negative disconfirmation. Finally, our results *enhance IS theories* by offering both a new context for exploring expectation confirmation/ disconfirmation as well as deeper insights into what cognitive functions may come to bear when these conditions are experienced by ENP users.

2 Theoretical Background & Related Work

2.1 ENP Information Filtering

IS research on ENPs has examined the factors that influence how and why knowledge is both contributed (Wasko et al., 2004, 2009; Wasko & Faraj, 2005) and, more recently, consumed (Fadel et al., 2015; Meservy et al., 2014, 2019) on ENP forums. The present study focuses on the consumption side of the knowledge exchange equation. Recent IS research has made inroads in understanding behaviors associated with ENP information filtering. Much of this work draws on dual-process theories of human cognition (e.g., Eagly & Chaiken, 1984; Petty & Cacioppo, 1986), which posit that information processing can occur via a central (systematic) route in which information content is carefully scrutinized, or via a peripheral (heuristic) route in which quicker and easier judgments are reached based on surrounding contextual cues. Studies have shown that both information content and contextual cues play an important role in the information filtering process. For example, Meservy et al. (2014) showed that although greater elaboration of information content positively moderated its effect on filtering decisions, contextual cues exerted an even larger influence on these decisions, even among ENP knowledge seekers with the ability and motivation to analyze information content. Fadel et al. (2015) examined how attentional switching patterns between solutions vs. between different cues within the same solution affected filtering decisions, with results suggesting that greater filtering accuracy is associated with systematic comparisons of solution content and increased attribute-based filtering over time. Finally, Meservy et al. (2019) showed that filtering judgments were influenced by the valence and source of contextual cues, as well as an interaction between different types of cues and the solution content itself. Using an fMRI experimental protocol, Meservy et al. (2019) also offer preliminary propositions surrounding differential neural systems recruited during the information filtering process.

Although the studies cited have begun to shed light on how information found on ENP forums is filtered and evaluated, several important theoretical questions remain, including how combinations of contextual cues and content interact to influence filtering judgments. In this study, we rely on two theoretical perspectives to guide our investigation of this question. First, expectation confirmation theory (Oliver, 1980, 2010) offers a useful lens for understanding how expectations and their subsequent confirmation/disconfirmation via experiences influence outcome evaluations. Second, prospect theory (Kahneman & Tversky, 1979) provides a theoretical rationale for explaining differential outcomes based on positive vs. negative expectation disconfirmation.

2.2 Expectation Confirmation Theory

Expectation confirmation theory (Oliver, 1980, 2010) has been widely applied in IS research to explain user satisfaction with and continued use of information systems (e.g., Brown et al., 2014; Lankton & McKnight, 2012). Originating in the domain of marketing and consumer behavior, this theory postulates that satisfaction and subsequent outcome evaluations with regard to an artifact are a function of initial expectations about that artifact that are either confirmed or disconfirmed by experience. Research has shown, for example, that both satisfaction and continued use of an information system are positively influenced by the degree to which expectations about an information system are exceeded in a positive direction (termed positive disconfirmation) vs. when they are unmet (termed negative disconfirmation) (Bhattacherjee, 2001; Bhattacherjee & Premkumar, 2004).

Table 1. Six Models of Expectation Confirmation

Model	Explanation of expectation confirmation	Sample IS studies
Assimilation	Experiences assimilate to expectations. Outcome evaluations are highest (lowest) when expectations are high (low).	(Lankton & McKnight, 2012; Szajna & Scammell, 1993)
Contrast	The contrast of expectations and experiences leads to more extreme outcome evaluations. Evaluations are highest (lowest) when experiences positively (negatively) disconfirm expectations.	(Staples et al., 2002)
Assimilation-Contrast	When the gap between expectations and experiences is small, outcome evaluations assimilate to expectations. When the gap is large, positive (negative) disconfirmation produces the highest (lowest) outcome evaluations.	(Brown et al., 2012; Goode et al., 2017; Masuch et al., 2019)
Generalized Negativity	Any departure of experiences from expectations has a negative effect on outcome evaluations. Evaluations are highest when expectations are met.	(Ginzberg, 1981; Goode et al., 2017; Tan et al., 1999; Venkatesh & Goyal, 2010)
Expectations Only	Expectations directly predict outcome evaluations; experiences are irrelevant.	(Davis et al., 1989; Köbler et al., 2011)
Experiences Only	Experiences directly predict outcome evaluations; expectations are irrelevant.	(Brown et al., 2008; Hakkarainen, 2013; Medina et al., 2015)

Although the fundamental concept of expectation confirmation/disconfirmation is straightforward, the interplay between expectations and experience and their effect on subsequent outcomes is not universal. Literature in consumer behavior (e.g., Anderson, 1973; Schifferstein et al., 1999) as well as IS (e.g., Brown et al., 2014) has identified at least six theoretical models that offer competing accounts of expectation confirmation: assimilation, contrast, assimilation-contrast, generalized negativity, expectations only, and experiences only. The following paragraphs describe the key tenets of each these models, which are summarized in Table 1 (adapted from Brown et al., 2014).

The *assimilation* model of expectation confirmation holds that expectations serve as an anchor to experiences such that the evaluation of experiences assimilates toward expectations. When expectations are high (low), outcome evaluations tend to be higher (lower) to reduce the cognitive dissonance between expectations and experiences (Brown et al., 2014). This means that expectations should be set high to achieve the most positive evaluation of experiences (Boulding et al., 1993). Conversely, the *contrast* model asserts that high or low outcome evaluations result not from the initial value of expectations per se, but from the contrast between these expectations and what is experienced (Staples et al., 2002). Under this account of expectation confirmation, outcome evaluations are highest when experiences markedly exceed expectations, and lowest when they fall markedly short of expectations. This would suggest that the positive disconfirmation of initially low expectations will produce the most positive outcome evaluation.

The *assimilation-contrast* model combines the assimilation and contrast perspectives. According to this model, the interplay between expectations and experience depends on the degree of separation between them (Klein, 1999). For small differences, outcome evaluations will assimilate toward experiences. As differences increase, the contrast weighs more heavily and produces the most extreme outcome evaluations: highest for positive disconfirmation and lowest for negative disconfirmation (Brown et al., 2014). Under this model, high outcome evaluations result from assimilation to moderately high expectations, or positive disconfirmation of very low expectations.

The fourth model, *generalized negativity*, offers a very different account of expectations and experiences. Under this model, *any* departure of experience from expectations results in a lower outcome evaluation. This model therefore predicts that outcome evaluations are highest when experiences (positive or negative) are consistent with expectations (confirmation) and lowest when they are inconsistent (disconfirmation) (Ginzberg, 1981; Venkatesh & Goyal, 2010).

The final two models posit that expectations and experiences do not interact in influencing outcome evaluations. The *expectations only* model holds that experiences do not affect outcome evaluations at all—only expectations matter (Davis et al., 1989). Outcome evaluations are therefore highest when expectations are high. In contrast, the *experiences only* model makes the opposite assertion: outcome evaluations are shaped only by experiences, regardless of initial expectations (Brown et al., 2008). Here, positive outcome evaluations are achieved only through positive experiences.

Over the past two decades, several studies in the IS literature have applied expectation confirmation theory to understand how expectations and experiences associated with an information system influence its subsequent use (e.g., Bhattacherjee, 2001; Bhattacherjee & Premkumar, 2004; Brown et al., 2012, 2014; Ginzberg, 1981; Lankton & McKnight, 2012; Staples et al., 2002; Szajna & Scammell, 1993; Venkatesh & Goyal, 2010). Results from this body of work have been mixed, with some studies finding support for each of the six models summarized above (see Brown et al., 2014 for a review). In their study, Brown et al. (2014) explicitly compared each of these six models using survey data that measured people's expected and experienced perceived usefulness of a system and its subsequent use. They concluded that in the domain of information systems use, "the assimilation-contrast model has the highest predictive ability and is the best available model for explaining the relationship between usefulness and key dependent variables in IS" (Brown et al., 2014, p. 749).

2.3 Prospect Theory

Prospect theory, a foundational theory of behavioral economics, suggests that human decision-making is asymmetrical with respect to anticipated gains and losses resulting from a decision (Kahneman & Tversky, 1979). In particular, when faced with a potential loss vs. a commensurately sized gain, people weigh the disutility of the loss disproportionately higher than the utility of the gain, and consequently go to greater lengths (or assume more risk) to avoid the loss than to achieve the gain. For example, most people would choose to win $500 with certainty than accept a 50% chance of winning $1000 or $0, even though the expected value of these two options is the same. However, faced with a certain loss of $500 or a 50% chance of losing $1000 or $0, most people choose the latter (riskier) option to avoid the certainty of loss (Chiu & Wu, 2011).

The predictions of prospect theory can be framed within the lens of expectation confirmation theory, where positively and negatively disconfirmed expectations are viewed as gains (getting more than one expected) or losses (getting less than one expected), respectively (Schifferstein et al., 1999). The asymmetry predicted by prospect theory means that the magnitude of a person's response to negative disconfirmation (a perceived loss) will be greater than the magnitude of a response to a comparable positive disconfirmation (a perceived gain). In other words, when people have high expectations about an object (e.g., an information system or information itself) and these expectations are unmet, the fallout from this negative disconfirmation is larger than the corresponding benefit of having expectations exceeded (Brown et al., 2014; Cheung & Lee, 2009; Lankton & McKnight, 2012).

A handful of studies in the IS literature have explored prospect theory as it relates to information systems adoption. For example, Lankton and McKnight (2012) found that negative disconfirmation of expectations surrounding an information system's usefulness (i.e., the system was less useful than expected) had a disproportionately stronger negative impact on user satisfaction with the system than the positive impact that occurred when expectations were exceeded. (Interestingly, an opposite positive asymmetry was observed for expectations surrounding ease of use.) Similarly, Cheung and Lee (2009) showed that negative perceptions of qualities such as information accuracy, timeliness, and appropriateness had a stronger deteriorating effect on user satisfaction with an online portal than the satisfaction-enhancing effect of similarly-scaled positive perceptions. Principles of prospect theory have also been observed in other areas of IS research, including software project escalation (Keil et al., 2000), continuance (Newman & Sabherwal, 1996), and investment (Rose et al., 2004).

2.4 Prediction Errors

Expectation confirmation and prospect theories offer useful insights into *behaviors* resulting from expectation confirmation/disconfirmation, but what happens in the brain when expectations are violated has also been a topic of ongoing interest to neuroscience researchers. Expectation confirmation/ disconfirmation has been explored in a variety of contexts in both human and animal neurocognitive studies, including pattern recognition (Bubic et al., 2009), reward prediction (Martin et al., 2009), and reasoning about ontological and causal relationships (Danek et al., 2015; Porubanova et al., 2014). Studies in this area typically identify expectation violation as a form of *prediction error*, defined as the difference between an expected (predicted) and actual outcome (Schultz, 2016; Schultz & Dickinson, 2000). Prediction errors can be either positive (i.e., the actual outcome varies from expectations in a positive way) or negative (i.e., the actual outcome varies from expectations in a negative way) (Asaad & Eskandar, 2011). In an ENP forum context, prediction error (expectation disconfirmation) would occur when expectations formed about the quality of a forum solution based on contextual cues are later violated (either positively or negatively) through an examination of solution content.

Neurobiological studies exploring prediction error in different contexts have exhibited some divergence in observed patterns of neural activity depending on the context in question; however, meta-analyses of this body of work have converged on certain brain areas that seem to reliably activate across different types of prediction error scenarios. For example, in their review of 35 neural studies involving reward prediction error paradigms, Garrison et al. (2013) identified the striatum, anterior cingulate cortex (ACC), and the lateral prefrontal cortex as areas commonly associated with prediction error. A more recent meta-analysis by D'Astolfo and Rief (2017, p. 4) revealed similar findings: prediction error was associated with activation changes in the striatum, insula, thalamus, and fronto-medial structures (such as the ACC): areas that are associated with the fronto-striatal circuit which is commonly assumed to be "involved in expectation violation processing and the resulting expectation and behavioral adaptation." These findings may be due to the role of the ACC in error detection (Carter et al., 1998), the role of the striatum in signaling reward anticipation and prediction error (O'Doherty, 2004), and the role of the prefrontal cortex in monitoring ongoing behavior and updating goals based on feedback (Miller & Cohen, 2001).

In the following section, we draw from tenets of expectation confirmation theory, prospect theory, and neural response to prediction errors to develop our research hypotheses. We first hypothesize about patterns of filtering *behaviors* when expectations based on contextual cues are confirmed or disconfirmed. Then, integrating neurobiological evidence related to prediction errors, we hypothesize about the *neural mechanisms* that underlie these behaviors.

3 Hypotheses

As noted earlier, the central premise of our theorization is that ENP knowledge seekers can form initial expectations about the utility of a solution based on contextual cues, and these expectations can be confirmed or disconfirmed by subsequent evaluation of solution content. This premise is supported by extant ENP research, which has shown that because contextual cues are quickly and easily consumed, they can form the basis of initial judgments about solutions even for those experienced and knowledgeable enough to evaluate solution content itself (Meservy et al., 2014). For the purposes of our theorization, we consider a prototypical case where contextual cues set high (H) or low (L) expectations for the quality of the solution, and the content quality of the solution itself is either high (H) or low (L). Combining these conditions produces four possible outcomes: two in which expectations are confirmed as high (HH) or low (LL), and two in which expectations are disconfirmed, either positively (LH) or negatively (HL). For example, a knowledge seeker who sees that a solution is highly rated (H) by a subject matter expert and/or other participants on the ENP forum may reasonably expect that the quality of the solution (i.e., its correctness and utility for solving the problem) will be high (H). If the subsequent evaluation of solution content fails to identify any flaws in the solution or if there is enough evidence to indicate that the solution solves the problem, this expectation may be confirmed (HH), and the user will likely decide to adopt the solution. However, if the user perceives an error or other problem with the solution after examining its content (HL), then negative disconfirmation occurs, and the user's initial high expectations of quality will be tempered. Similar outcomes can occur for the negative side: expectations about solutions whose contextual cues indicate lower quality (e.g., community downvotes or expert critiques), may subsequently be confirmed by verification of flaws within the solution (LL) or positively disconfirmed if the solution itself appears to be viable (LH).

The six models of expectation confirmation outlined earlier predict different outcomes for expectation (dis)confirmation in ENP information filtering tasks. The assimilation model predicts that experiences assimilate to expectations and, therefore, prescribes that expectations should be set high (Boulding et al., 1993). Under this model, judgments (i.e., experiences) of information quality based on examination of the information content are swayed by initial expectations based on contextual cues and should be most extreme when these judgments confirm expectations. In other words, the solutions most (least) likely to be adopted are those whose high (low) initial expectations—based on contextual cues—are subsequently *confirmed* by evaluation of solution content (HH, LL), whereas evaluation of solutions whose content *disconfirms* initial expectations (HL, LH) will be more moderate due to the anchoring effect of these expectations (Lankton & McKnight, 2012; Szajna & Scammell, 1993). This outcome is depicted graphically in Figure 1(a) below. In the figure, initial expectations about solution quality (shown on the left) may be high or low[1] depending on the initial indications of contextual cues. When the individual then evaluates the actual solution content, new judgments are formed (shown on the right) that may confirm or disconfirm expectations. If no assimilation occurs, the final judgments about high-quality solutions should be the same whether expectations are confirmed (HH) or disconfirmed (LH), and the same should be true for low-quality solutions (LL and HL). However, if assimilation is present, the final evaluations of high-quality solutions initially expected to be of low quality should be lower than those expected to be of high quality due to assimilation toward lower initial expectations (the inverse would hold for low-quality solutions).

[1] We consider boundary conditions for theoretical exposition, though more moderate judgments are also possible.

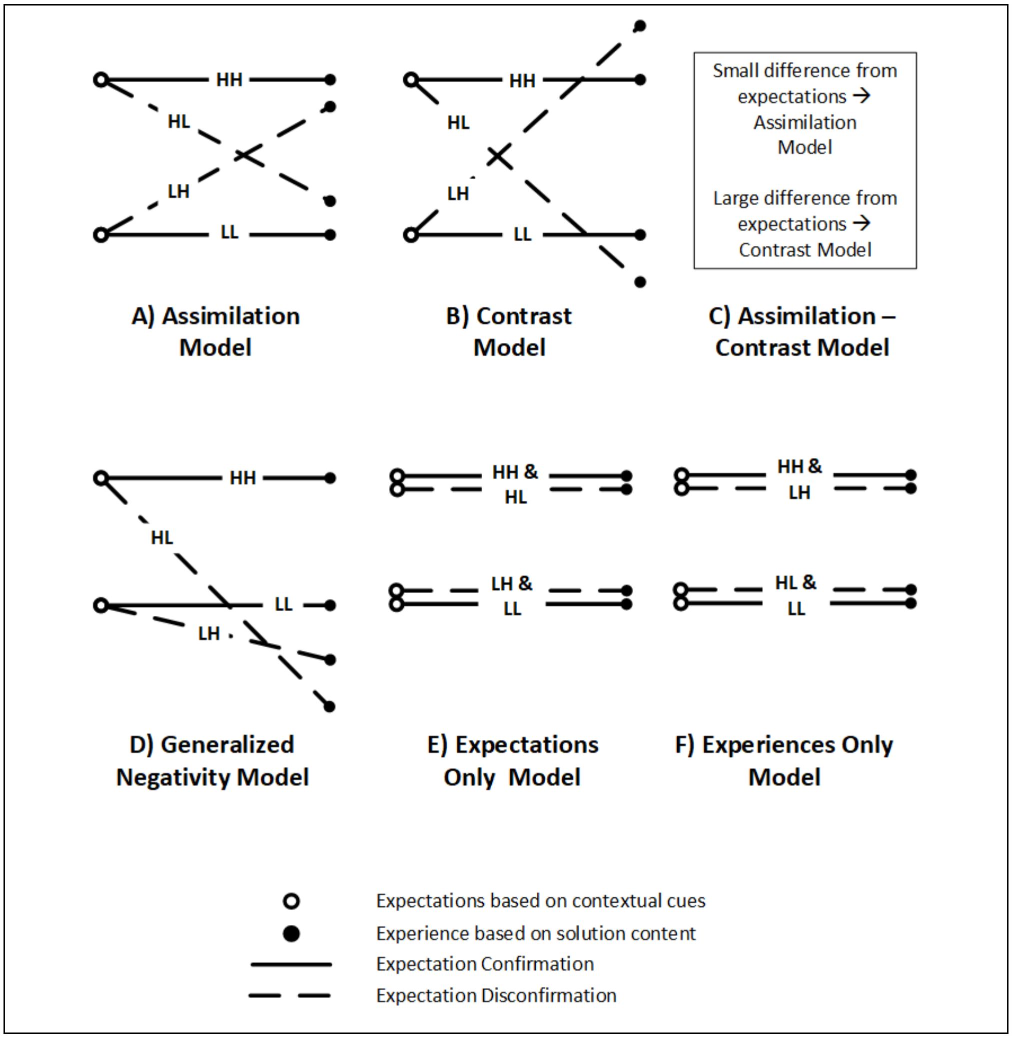


Figure 1. Expectation Confirmation/Disconfirmation Models

Counter to the assimilation model, the contrast model predicts that the highest or lowest outcome evaluations occur under conditions of disconfirmation, i.e., when the difference between expectations and experiences is the largest in either a positive or negative direction (Staples et al., 2002). Under this model, solutions that are eventually rated highest by ENP users should be those where initial low expectations based on peripheral cues are positively disconfirmed (exceeded) by evaluation of the content itself, and vice versa for low-quality solutions initially expected to be of high quality. Under this model, depicted graphically in Figure 1(b), the contrast between expectations and experiences creates an amplifying effect wherein experiences that disconfirm expectations are evaluated as more extreme (high or low) than those that confirm expectations. This would suggest that expectations should be set low to produce high outcome evaluations.

The assimilation-contrast model, as its name suggests, combines predictions from the assimilation and contrast model. As indicated in Figure 1(c), this model holds that for small departures from expectations, experiences will assimilate to expectations. However, as the distance between expectations and experience increases, the effect of surprise/disappointment from exceeded/unmet expectations becomes stronger, and the contrast effect manifests itself (Brown et al., 2012). For ENP users, this would suggest that when the differences between contextual cue-based expectations and content-based experiences are small, evaluation of solution content will assimilate toward cue-based expectations. When solution content quality is perceived to be markedly higher (or lower) than initially expected, this surprise effect will produce more extreme outcome evaluations consistent with the contrast model. This suggests that outcome evaluations are highest when expectations are slightly high, accurate, or extremely low (Brown et al., 2014).

Unlike the assimilation and contrast model, the generalized negativity model posits that *any* departure of experience from expectations will result in a lower outcome evaluation; that is, both positive and negative disconfirmation will result in lower outcome evaluations than either positive or negative confirmation (Ginzberg, 1981; Venkatesh & Goyal, 2010). As shown in Figure 1(d), this means that final evaluations of solution quality would be higher when evaluations of solution quality confirm contextual cue-based expectations whether these expectations are high or low. Under this model, expectations should be set accurately to achieve the highest outcome evaluations.

The final two models, expectations-only and experiences-only, posit that expectations and experiences do not interact. Under the expectations-only model, outcome evaluations are shaped only by expectations; experiences are irrelevant (Davis et al., 1989). In ENP information filtering, this would mean that judgments are based solely on indications of contextual cues; evaluation of solution content would not alter these judgments. On the other hand, the experiences-only model holds that expectations do not matter—outcome evaluations are determined only by experiences (Brown et al., 2008). This would imply that ENP users ignore indications of contextual cues and base their judgments only on evaluations of solution content. Figures 1(e) and 1(f) depict these patterns. In the expectations-only model, judgments are uniform for any condition where contextual cues are the same (HH and HL, LL and LH); in the experiences-only model, judgments track with the evaluations of solution content (HH and LH, LL and HL).

Research in both IS and other domains has provided support for each of the six models of expectation confirmation in various domains; however, due to the paucity of such research in the domain of ENP forums, it is unclear which of these models offers the most accurate theoretical account of information filtering behaviors based on expectations and experiences. Previous research in ENP information filtering provides strong evidence that both contextual cues and solution content exert influence on the information filtering process (Fadel et al., 2015; Meservy et al., 2014); thus, it seems unlikely that the expectations-only model (based exclusively on contextual cues) or the experiences-only model (based exclusively on solution content) would hold in this context. However, the assimilation, contrast, generalized negativity, or assimilation-contrast models of expectation confirmation each entail a role for both expectations and experiences, and each offer a plausible but unique explanation of how they might interact in ENP information filtering. Accordingly, in the absence of empirical data favoring one model in this context, we test a hypothesis of competing alternatives:

H1: In ENP information filtering, expectations based on contextual cues interact with experiences based on solution content in a pattern consistent with either (a) assimilation, (b) contrast, (c) generalized negativity, or (d) assimilation-contrast models of expectation confirmation.

Theories of human decision-making offer insights not only into the anticipated outcomes of confirmed and disconfirmed expectations, but also regarding the asymmetric impact of the valence of these expectations. In the context of expectation confirmation, asymmetry refers to the condition in which the effect of positive or negative disconfirmation on the outcome variable is disproportionately larger or smaller than the other, suggesting a nonlinear relationship between expectations, experiences, and outcome variables. Expectation confirmation research in IS (Cheung & Lee, 2009; Lankton & McKnight, 2012) and in other domains (Schifferstein et al., 1999) has typically provided evidence for negative asymmetry, meaning that the diminishing effect of negative disconfirmation on an outcome variable is disproportionately larger than a commensurate amplifying effect of positive disconfirmation. For example, research has shown that the negative disconfirmation of expectations about the usefulness of an IS has a larger negative impact on user satisfaction with the system than the corresponding positive impact from positive disconfirmation (Cheung & Lee, 2009; Lankton & McKnight, 2012).

The asymmetry associated with expectation disconfirmation is rooted in prospect theory (Kahneman & Tversky, 1979), which holds that when making judgments, people weigh potential losses more heavily than they weigh equivalent gains. In other words, a course of action that would lead to avoidance of a loss would generally be preferred to one that produces a commensurate gain. As explained by Lankton and McKnight (2012, p. 94), "not responding to something that might have positive outcomes has less dire consequences (e.g., mere regret) than responding to something that might have negative outcomes (e.g., actual harm)." Applying this concept to the context of ENP filtering, we might expect that a solution favored by the indications of contextual cues but then found to be of low quality (an unexpected loss), will evoke a greater adjustment in judgment than a solution initially signaled as low quality that is later deemed to be viable (an unexpected gain). That is, people will adjust their filtering judgments more dramatically to avoid a loss (adopting a bad solution) than to achieve a gain (adopting a good solution). Importantly, this prediction that the upward adjustments of positive disconfirmation will be more modest than the downward adjustments of negative disconfirmation is distinct from that of the generalized negativity model, which holds that any departure from expectations will be negative.

H2: When evaluation of content is inconsistent with expectations based on contextual cues, evaluation adjustments will be larger for a negative disconfirmation (an unexpected loss) than for a positive disconfirmation (an unexpected gain).

Hypotheses 1 and 2 posit that different combinations of cues on ENP forums will lead to different types of filtering *behaviors*; however, equally important are the neural mechanisms that underlie these behaviors. Elucidating the neural generators of these behaviors can help advance theory beyond explaining *what* happens during ENP filtering to explaining *why* these behaviors occur. We therefore turn our attention to the neural correlates of expectation (dis)confirmation that may provide explanatory insights to forum information filtering behaviors.

Summative studies of brain research employing prediction error paradigms have pointed to several brain regions possibly associated with the processing of prediction errors, including the ACC, insula, prefrontal cortex, the striatum, and the midbrain (D'Astolfo & Rief, 2017; Garrison et al., 2013). To narrow these broad regions of interest in a systematic way, we performed a meta-analysis using the Neurosynth database (neurosynth.org) and the search term "prediction error." Neurosynth scrapes the PubMed Central database (maintained by the US National Institutes of Health) for fMRI publications that report locations of activations resulting from contrasts associated with specific terms and returns brain locations that are associated with a given term. The ACC, left and right anterior insula, left and right ventral striatum, and the midbrain (presumably the ventral tegmental area or VTA) were all identified as associated with contrasts of "prediction error" (in what Neurosynth terms a "uniformity test"). However, the ACC and anterior insula likely signal errors generally, while the ventral striatum and VTA, identified as *preferentially* associated with prediction error, may be more specifically involved in evaluating positive and negative prediction errors (see below). In this hypothesis, we therefore focus on brain regions that have only been shown to be involved in expectation disconfirmation generally, and not specifically associated with either positive or negative disconfirmation. Consequently, we hypothesize that brain regions that signal errors generally would be more active when there is a prediction error (regardless of whether the error is positive or negative) as in the case where ENP solution quality is inconsistent with contextual cues versus the case where there is no prediction error:

H3: Distinct neural activation patterns will be observed when expectations (predictions) based on contextual cues are confirmed vs. when they are disconfirmed. Specifically, there will be a higher BOLD signal in the ACC and anterior insula when there is a prediction error compared to when there is no prediction error.

In connection with H2, neuroscience research also offers some evidence for differential neural substrates corresponding to positive and negative prediction error. For instance, in a study that involved probabilistic reversal learning tasks (tasks where stimuli associated with success and failure outcomes are repeatedly reversed), Meder et al. (2016) found that positive prediction errors were coded by the ventral striatum and the medial frontal cortex, a finding corroborated by earlier work examining valenced prediction errors (Hauser et al., 2015; Iglesias et al., 2013). D'Ardenne et al. (2008) used primary rewards (liquid delivered to thirsty participants) and found decreased activation in the ventral striatum for negative prediction errors relative to positive prediction errors. The pattern of increased activation for positive prediction errors relative to negative prediction errors in the ventral striatum and VTA has been replicated numerous times (e.g., Abler et al., 2006; see Wang et al., 2016 for review); however, error-related processing in response to informational rewards such as online solutions has received less attention. These findings of differential activation for positive and negative prediction error are consistent with the results of our Neurosynth meta-analysis that identified the ventral striatum and VTA as *preferentially* associated with contrasts of "prediction error," indicating that activation in the ventral striatum and VTA should distinguish between positive and negative prediction errors. Drawing from this work, we anticipate similar activation differences when knowledge seekers experience positive prediction error (encountering a solution that is unexpectedly good despite negative contextual cues) vs. negative prediction error (encountering a solution that is unexpectedly bad despite positive contextual cues) on an ENP forum.

H4: Distinct neural activation patterns will characterize the processing of negative prediction errors (unexpected losses) vs. positive prediction errors (unexpected gains). Positive prediction errors (solution quality higher than indicated by contextual cues) will be associated with a higher BOLD signal than negative prediction errors in the ventral striatum and in the VTA. Further, we hypothesize a higher BOLD signal in these same regions for no prediction error than for a negative prediction error.

4 Methodology

We selected programming as our experimental context, as software developers often search online forums to find solutions. To evaluate our hypotheses, we conducted a controlled experiment where participants were presented with solutions to programming problems on a mock ENP forum and were asked to evaluate the solutions and render a judgment as to whether each would solve the problem at hand. The experiment was conducted in a magnetic resonance imaging (MRI) scanner (a 3T Siemens TIM Trio scanner using a 12-channel head coil) so that we could measure participants' brain activity as they evaluated the solutions.

4.1 Experimental Instrument and Measures

We developed a custom experimental instrument that mimicked the appearance and content of actual online ENP forums. Six common programming problems (e.g., sorting an array, reversing a string) were selected, and eight distinct solutions were developed for each problem. To manipulate the quality of the solutions, we found eight valid solutions for each problem on actual online forums and then introduced logical and other errors into half of the solutions to ensure that they would not solve the problem. Thus, each programming problem had four high-quality and four low-quality solutions. All solutions were standardized to a common programming language (C#).

The instrument paired each of the solutions described above with two contextual cues: an indicator of whether the solution had been validated by a domain expert (expert validation) and an indication of whether the solution had been validated by the larger population of ENP participants (community validation). Using a thumbs-up/thumbs-down model, the valence of these cues was either positive (suggesting a high-quality solution) or negative (suggesting a low-quality solution). This produced four treatment conditions: contextual cues that were either positive/high (H) or negative/low (L) paired with either high-quality (H) or low-quality (L) solutions (HH, HL, LH, and LL).[2] Additional contextual information like screen names, avatars, and join dates were taken from actual online forums to increase the face validity of the instrument. To minimize the potential exogenous influence of these factors, screen names, avatars, and join dates were randomly associated with different solutions across all participants such that this contextual information would not be more likely for one condition, problem, or solution than for another. Screen names and avatars were only paired with a single solution and never repeated.

The experimental instrument allowed us to capture both behavioral and cognitive measures during information filtering. To isolate the behavioral impact of contextual cues, we first presented the cues by themselves with the code blurred such that the participant could tell that a solution existed but could not see the details of the code (phase 1). We displayed contextual cues first because previous studies have found that those cues are often used in filtering potential solutions before evaluating content cues (Fadel et al., 2015; Meservy et al., 2014). After evaluating the cues alone, participants provided a rating of how likely they would be to adopt the solution on a 5-point scale ranging from unlikely to likely. Following this rating, the code was unblurred (phase 2), enabling the participant to evaluate the solution content itself. Participants could then adjust their initial rating of the solution if they wished. The phase 1 and phase 2 ratings obtained for each treatment condition (HH, HL, LH, and LL) were used to test hypotheses H1 and H2. Participants had up to 30 seconds to complete both phases for each solution but were not constrained to a certain amount of time in either phase. On average, participants spent 4.7 (SD = 2.2) seconds on phase 1 and 16.5 (SD = 6.1) seconds on phase 2. Figure 2 shows a sample stimulus for phase 1. Appendix A contains additional information about the experimental procedure and a sample stimulus for phase 2.

To measure cognitive activity associated with H3 and H4, we measured hemodynamic brain response during the experimental task using an MRI scanner. We followed guidelines established in NeuroIS literature (Brocke & Liang, 2014; Dimoka, 2011) for conducting and reporting an fMRI study. Similar to other studies of prediction error, we analyzed the hemodynamic response during phase 2 of each trial from the onset of the display of the programming solution to the response of the participant to capture the neural processes associated with outcome evaluation. See Appendix B for MRI scan parameters and details of MRI data analyses.

4.2 Participants and Procedure

To test and refine the experimental instrument, we first conducted a pilot study with six experienced software developers. This pilot test allowed us to verify the effectiveness of the experimental manipulations and make minor alterations to improve clarity in process and content. We then recruited experienced software developers from the local community to participate in the experiment. Participants were screened to ensure safety and compatibility with the MRI machine and to ensure they were proficient in Java, C#, or C++ and had at least one year of programming experience. In total, 29 participants (93.1% male, average age 26.2 years, average of 4.0 years of programming experience) were recruited from local companies and compensated with either $25 or a digital 3D model of their brain.

When participants arrived at the MRI center, they were shown an introductory video that provided an overview of the study, an introduction to the problems they would try to solve, how they would provide their answers, and also a brief overview of safety concerns related to MRI studies.

[2] Our stimuli also included four additional conditions where contextual cues were inconsistent with each other (one positive, one negative); however, in this paper, we only consider solutions where contextual cues were congruent in their indications. See Appendix A for additional details on the complete data that was collected.

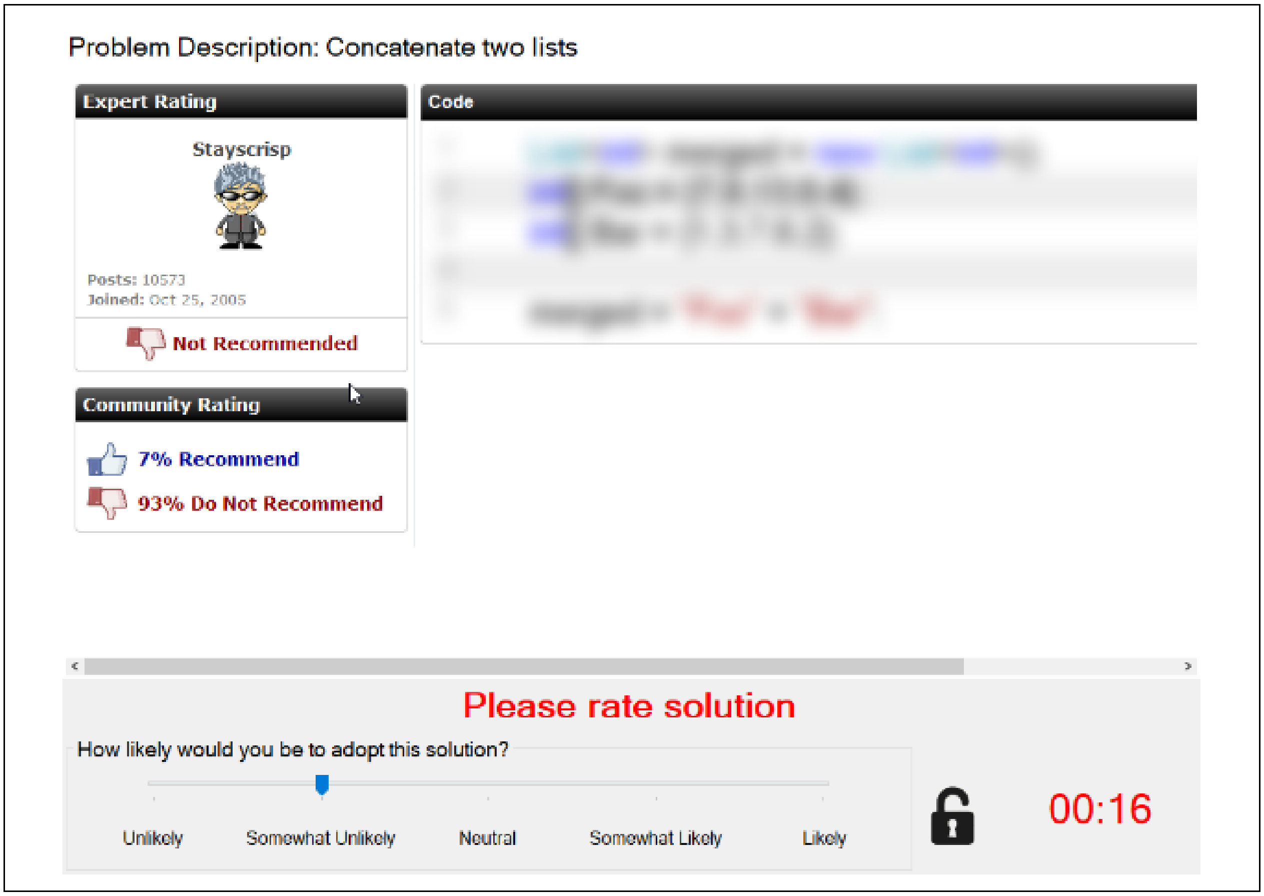


Figure 2. Sample Phase 1 Stimuli: Rating Based on Contextual Cues

Researchers then answered any questions before situating participants in the MRI machine, where participants interacted with the instrument using a four-button controller and communicated with the researchers via a microphone and headphones. First, a structural scan was captured so that fMRI signal data could later be co-registered with specific areas of the brain. Next, participants went through a training session to become further acclimated to the task and how to interact with the experimental instrument. After training, researchers answered any questions the participant may have had. Then, each of the programming problems and their associated potential solutions were presented. Solutions were grouped by problem to decrease switching costs between problems. All other aspects of the experiment were fully randomized, including the overall order of the problems, the order of the solutions within each problem, the pairing of contextual cues (positive or negative) with code quality (high or low), the avatars, screen names, other information of the expert providing the validation of the solution, etc. The programming problems were broken into two blocks of three problems each in order to give the participant an opportunity to rest and avoid fatigue. Between blocks, participants saw a blank screen with a plus sign in the middle, as is common when separating stimuli in an fMRI experiment (Huettel et al., 2003). After the experiment, participants completed a survey about their experience, including familiarity with and perceived difficulty of the programming problems presented.[3]

5 Analysis and Results

We employed two types of analysis to test our hypotheses. To measure filtering behaviors associated with H1 and H2, we estimated a series of linear mixed-effects models using the lmer function in the lme4 package (version 1.1-23) in R (version 4.0.2; Bates et al., 2015) to compare solution ratings across treatment conditions and phases.[4] Because each solution was

[3] Familiarity was measured on a 5 point scale ranging from 1-Not familiar at all to 5-Extremely Familiar. Difficulty was measured on a 7 point scale from 1-Extremely easy to 7-Extremely difficult. Participants reported an average familiarity of 3.94 (*SD*: 0.95) and an average difficulty of 2.44 (*SD*: 1.16).

[4] Strictly speaking, our dependent rating variable was measured on an ordinal (Likert) scale. Although there is support for using linear mixed-effects models with this type of data (Kizach, 2014; Norman, 2010), as a robustness check we also conducted a parallel analysis using the Cumulative Link Mixed Models (CLMM) function of the ordinal

evaluated by each participant, the models included random intercept terms for solution and participant. We also controlled for participant characteristics, including gender, age, educational level, years of experience, and programming knowledge, problem familiarity, and problem difficulty. None of these variables had a significant effect except for gender and problem familiarity. Ratings provided by women were somewhat lower than those provided by men and were slightly higher for problems with which participants were more familiar. However, inclusion of the control variables did not significantly improve the fit of the model ($\chi2 = 13.839$, $p = 0.054$) or alter the significance pattern of the main effects. Appendix C provides regression coefficients and fit indices for both models.

H1 posited a competing alternatives hypothesis between assimilation, contrast, assimilation-contrast, and generalized negativity accounts of expectation confirmation in ENP information filtering. We ran several analyses to test this hypothesis. First, all of the models in H1a-d posit an interaction between expectations and experiences. To test for such an interaction, we estimated a two-way linear mixed effects model that compared the changes in solution ratings between phase 1 and phase 2 for each of the different treatment conditions, as well as the differences between ratings among conditions within each phase. Omnibus test results showed a statistically significant interaction between phase and condition on the final rating ($F (3, 1388) = 204.98$, $p < 0.001$). Post hoc mean comparisons using a Tukey multiple comparisons correction revealed significant differences both within and across phases (see Tables 2 and 3). In phase 1, where participants made judgments based only on the contextual cues, mean ratings for the HH and HL conditions were not significantly different from each other ($t = -0.350$, n.s.) as expected; similar results were observed for the LL and LH conditions ($t = -0.353$, n.s.). However, ratings for both of the high contextual cue conditions were significantly higher than those of the low contextual cue conditions, as shown in the unshaded areas of Tables 2 and 3. In phase 2, where participants were exposed to the solution content, results showed significant differences in the mean ratings between all conditions, with mean ratings decreasing from 4.21 (HH) to 3.21 (LH) to 2.32 (HL) to 1.52 (LL) (see gray shaded areas of Tables 2 and 3). These results substantiate the expected effects of our experimental manipulations and provide evidence that each combination of contextual cues and solution content quality has a unique effect on information filtering decisions, suggesting an interaction effect between these forum elements that would not be consistent with an expectations- or experiences-only account of expectation confirmation.

To ascertain which type of expectation confirmation model (assimilation, contrast, assimilation-contrast, generalized negativity; H1a-d) most closely accounted for the interaction between expectations and experiences in an ENP forum context, we examined the between-phase ratings within each condition (reported in the diagonal of Table 3) in conjunction with the comparisons reported above. Comparisons showed that the change in ratings between phases for the confirmation conditions (HH and LL) were nonsignificant; ratings did not change substantially when evaluation of code confirmed the indications of contextual cues. In contrast, ratings did change significantly for the disconfirmation conditions (HL and LH), with HL ratings decreasing by 2.05 in phase 2 ($t = -19.265$, $p < 0.001$) and LH ratings increasing by 1.67 ($t = 15.703$, $p < 0.001$). In both disconfirmation cases, final ratings moved toward the actual code quality; however, these adjustments did not produce final ratings that were equivalent to or more extreme than those of the corresponding confirmation conditions. Thus, our results fail to support either a contrast (H1b) or general negativity (H1c) account of expectation disconfirmation in this context (see Figure 1). Instead, as shown in Figure 3, final ratings for the disconfirmation conditions were more moderate than those of the corresponding confirmation conditions. This suggests that the contextual cues created an anchoring effect to final judgments about solution quality, a pattern that is consistent with either an *assimilation* (H1a) or *assimilation-contrast* (H1d) account of expectation confirmation.

Distinguishing between assimilation (H1a) or assimilation-contrast (H1d) models requires examining the size of the gap between expectations and experiences. As noted earlier, although both assimilation and assimilation-contrast accounts suggest that assimilation to expectations occurs, the latter posits that contrast effects manifest themselves as the differences between expectations and experiences grow. In our dataset, evidence for an assimilation-contrast model would exist if final phase 2 ratings for the disconfirmation conditions (HL and LH) were *more extreme* than the corresponding confirmation conditions (LL and HH, respectively) in cases where there was a large gap between initial expectations and the final content-based solution evaluation (see Figure 1c).

package (version 2019-12.10) in R (version 4.0.2) (Christensen, 2015; Team, 2017) to estimate ordinal mixed effects regression models with both fixed and random effects. The pattern of results from this analysis were identical to those obtained using lmer. Because the lmer coefficients correspond to mean rating values for each condition and thus offer a more straightforward interpretation, we report the results of this analysis.

Table 2. Mean Ratings and 95% Confidence Intervals by Phase and Condition

	Phase 1				Phase 2				
Condition	**Mean**	**SE**	**Upper CI**	**Upper CI**	**Mean**	**SE**	**Upper CI**	**Upper CI**	**Phase difference**
HH	4.33	0.094	4.14	4.52	4.21	0.094	4.02	4.39	-0.12
HL	4.37	0.094	4.18	4.56	2.32	0.094	2.13	2.50	-2.05
LH	1.54	0.095	1.36	1.73	3.21	0.095	3.03	3.40	1.67
LL	1.59	0.094	1.40	1.77	1.52	0.094	1.33	1.70	-0.07

Table 3. T-Ratios of Ratings Contrasts by Phase and Condition

	HH	**HL**	**LH**	**LL**
HH	-1.133	15.110**	9.168**	21.510**
HL	-0.325	-19.265**	-7.160**	7.457**
LH	25.698**	22.603**	15.703**	13.562**
LL	21.924**	25.911**	-0.353	-0.648

**$p < 0.001$

Between-condition contrasts for Phase 1

Between-condition contrasts for Phase 2

Within-condition contrasts between phases (Phase 2 – Phase 1)

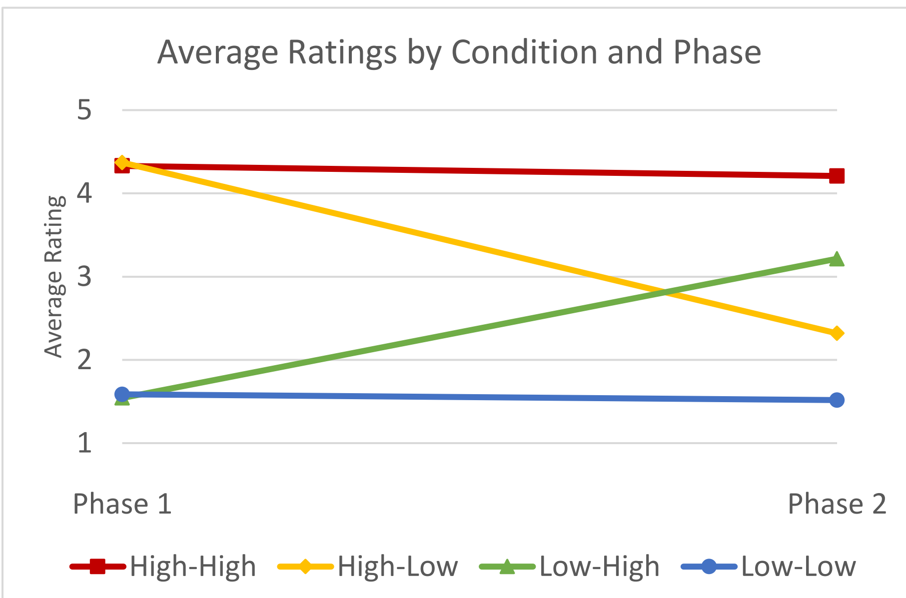


Figure 3. Ratings Pattern by Condition and Phase

Our experimental instrument allowed for a maximum expectations-experience gap measurement of 4 (difference between the highest possible rating of 5 and lowest possible rating of 1). Thus, to see whether such evidence existed, we isolated disconfirmation cases where the gap between phase 1 and phase 2 ratings was 3 or 4 (termed $HL_{large\text{-}gap}$ and $LH_{large\text{-}gap}$) and those where the gap was 1 or 2 (termed $HL_{small\text{-}gap}$ and $LH_{small\text{-}gap}$), and separately compared each of these groups to the confirmation conditions. Following the analysis above, we ran two-way linear mixed effects models that compared the changes in solution ratings between phases and conditions for each of the groups. The omnibus F statistic for the large-gap model was significant ($F(3, 998) = 466.23$, $p < 0.001$). Post hoc tests of mean ratings (Tables 4 and 5) showed that the contrasts between ratings for phase 1 were consistent with those reported earlier: differences existed only between the sets of high and low contextual cue conditions. In phase 2, however, the final rating for $HL_{large\text{-}gap}$ (1.13) was significantly *lower* than that of LL (1.52; $t = -3.389$, $p < 0.01$); the average final rating for $LH_{large\text{-}gap}$ (4.48) was *higher* than that of HH (4.21), though the difference was not statistically significant. Contrasts of within-condition ratings across phases were consistent with those reported earlier, with significant differences observed only for the disconfirmation conditions.

Table 4. Large-Gap Mean Ratings and 95% Confidence Intervals by Phase and Condition (disconfirmation conditions only)

	Phase 1				Phase 2				
Condition	**Mean**	**SE**	**Upper CI**	**Upper CI**	**Mean**	**SE**	**Upper CI**	**Upper CI**	**Phase difference**
HL	4.46	0.087	4.29	4.63	1.13	0.087	0.96	1.30	-3.33
LH	1.23	0.104	1.02	1.43	4.48	0.104	4.28	4.69	3.26

Table 5. T-Ratios of Large-Gap Ratings Contrasts by Phase and Condition

	HH	HL	LH	LL
HH	-1.469	29.451^{**}	-2.261	30.719^{**}
HL	-1.089	-29.304^{**}	-25.517^{**}	-3.839^{*}
LH	27.055^{**}	24.586^{**}	23.668^{**}	24.903^{**}
LL	31.306^{**}	28.593^{**}	-3.002	-0.839

$^{**}p< 0.001$; $^{*}p< 0.01$

Between-condition contrasts for Phase 1 (white)
Between-condition contrasts for Phase 2 (grey)
Within-condition contrasts between phases (Phase 2 – Phase 1) (black)

For the small-gap model, the F statistic was also significant ($F(3, 952) = 34.73$, $p < 0.001$). The pattern of between-conditions contrasts for phase 1 again remained consistent, as did the between-phase contrasts for each condition (Tables 6 and 7). In phase 2, ratings for the disconfirmation conditions of $HL_{small\text{-}gap}$ (3.10) and $LH_{small\text{-}gap}$ (3.02) were not significantly different from each other. However, the average final rating for $HL_{small\text{-}gap}$ was significantly *higher* than that of LL (1.52), while the rating for $LH_{small\text{-}gap}$ was significantly *lower* than that of HH (4.21), similar to results observed in the original model.

Figure 4 provides a visual depiction of the ratings patterns observed for the large- and small-gap groups. Although one of the comparisons ($LH_{large\text{-}gap}$ vs. HH) did not meet the threshold of statistical significance, these results suggest a general pattern that is consistent with an *assimilation-contrast* (H1d) account of expectation-confirmation in ENP information filtering.

Drawing from prospect theory, H2 posited asymmetric effects of unexpected losses vs. unexpected gains in ENP information filtering. To test this hypothesis, we conducted a paired samples *t*-test comparing the rating adjustment for the positive disconfirmation condition (LH) to that of the negative disconfirmation condition (HL). This test showed that the change for HL was significantly greater than that for LH ($t = 3.40$, $p < 0.005$), suggesting that people adjusted their original context-cue-based judgments more drastically to avoid an unexpectedly bad solution than to adopt an unexpectedly good one. This provides support for H2.

To examine the neural activity associated with filtering scenarios (H3 and H4), we analyzed the fMRI imaging data using the Analysis of Functional Neuroimages (AFNI) suite of programs (Cox, 1996). We followed standard fMRI practices when analyzing neural data (Dimoka, 2011). To capture the neural responses to expectation confirmation/disconfirmation as well as unexpected gains and losses, we performed a series of repeated-measures analyses that contrasted brain activations during phase 2 of the experiment in conditions where the quality of the code was high or low and consistent or inconsistent with the indications of contextual cues.

H3 postulated neural activation differences in the ACC and anterior insula when expectations based on contextual cues were confirmed vs. disconfirmed by subsequent evaluation of solution content. To test this hypothesis, we performed an analysis of fMRI activation within brain regions identified in a meta-analysis of fMRI papers with contrasts labeled "prediction error," which identified the ACC and anterior insula as commonly associated with contrasts of that term (Figure 5). In the first analysis, we examined mean fMRI activation (beta-values) within each of the identified regions of interest (ROIs). We collapsed confirmation conditions (HH, LL) and disconfirmation conditions (HL, LH) with the hypothesis that BOLD activation would be higher for the disconfirmation conditions than for the confirmation conditions.

As shown in Table 8, we observed significantly higher activation for disconfirmation than confirmation in the left anterior insula ($t(28) = 2.105$, $p = 0.022$) and in the ACC ($t(28) = 2.319$, $p = 0.014$). In the right anterior insula activation for disconfirmation was numerically higher than for confirmation ($t(28) = 1.655$, $p = 0.055$) though the difference did not reach statistical significance.

Table 6. Small-Gap Mean Ratings and 95% Confidence Intervals by Phase and Condition (disconfirmation conditions only)

	Phase 1				Phase 2				
Condition	**Mean**	**SE**	**Upper CI**	**Upper CI**	**Mean**	**SE**	**Upper CI**	**Upper CI**	**Phase difference**
HL	4.08	0.132	3.82	4.34	3.10	0.132	2.84	3.36	-0.98
LH	1.83	0.115	1.60	2.05	3.02	0.115	2.79	3.24	1.19

Table 7. T-ratios of Large-Gap Ratings Contrasts by Phase and Condition

	HH	HL	LH	LL
HH	-1.273	7.521**	9.557**	24.944**
HL	1.735	-5.821**	0.488	11.285**
LH	19.958**	13.390**	8.216**	11.157**
LL	25.422**	17.806**	1.802	-0.727

Note: $^{**}p < 0.001$; $^{*}p < 0.01$

(white)	Between-condition contrasts for Phase 1
(grey)	Between-condition contrasts for Phase 2
(black)	Within-condition contrasts between phases (Phase 2 – Phase 1)

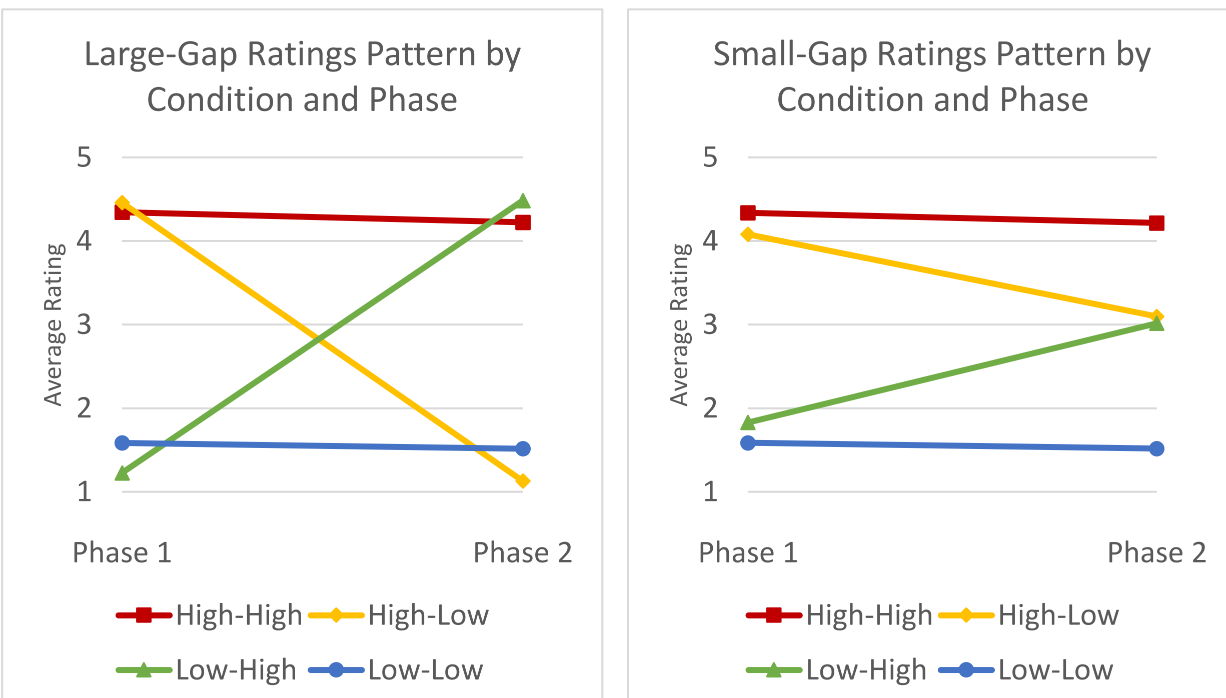
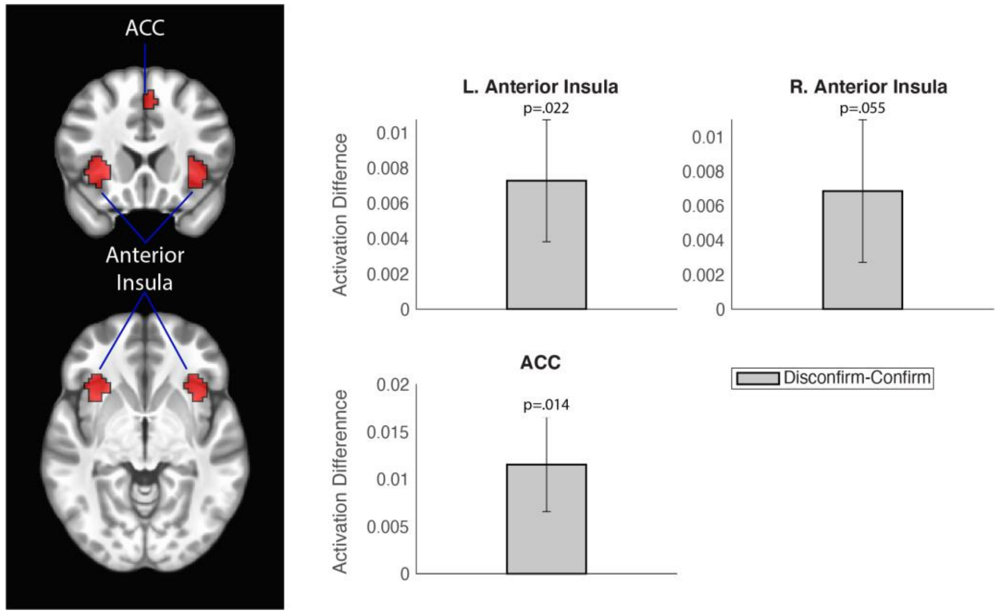


Figure 4. Ratings Pattern by Condition and Phase: Large Gap vs. Small Gap

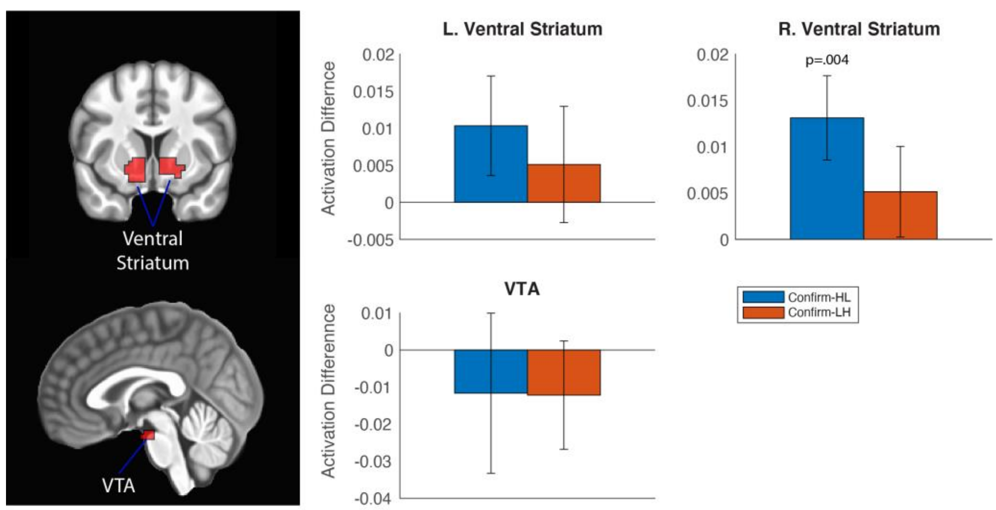
Table 8. Activation Differences between Confirmation and Disconfirmation in Anterior Insula and ACC

Region	Contrast	Mean difference	SD	T	Df	Sig. (1-tailed)
L anterior insula	Disconfirm – Confirm	0.00728	0.0186	2.105	28	0.022
R anterior insula	Disconfirm – Confirm	0.00686	0.02232	1.655	28	0.055
ACC	Disconfirm – Confirm	0.01153	0.02676	2.319	28	0.014



Note: Activation was higher for the disconfirmation condition than the confirm condition in the left anterior insula and ACC. Error bars ±SEM. L. = left; R. = right; ACC = anterior cingulate cortex

Figure 5. Regions of Interest Used to Test H3 (left) and fMRI Activation for the Contrast of Disconfirm-Confirm Conditions (right).



Note: Activation was higher for the confirmation condition than the HL (negative prediction error) condition in the right ventral striatum. Error bars ±SEM. L.=left; R.=right

Figure 6. Regions of Interest Used to test H4 (left) and fMRI Activation for the HL, LH and Confirm (HH, LL) Conditions (right)

Table 9. Activation Differences between Confirm and Positive and Negative Prediction Error in the Left and Right Ventral Striatum and VTA.

Region	Contrast	Mean difference	SD	T	Df	Sig. (1-tailed)
L Ventral Striatum	Confirm – HL	0.010	0.036	1.538	28	0.068
	Confirm – LH	0.005	0.042	0.651	28	0.261
R Ventral Striatum	Confirm – HL	0.013	0.024	2.887	28	0.004
	Confirm – LH	0.005	0.026	1.051	28	0.151
VTA	Confirm – HL	-0.012	0.116	-0.539	28	0.297
	Confirm – LH	-0.012	0.079	-0.834	28	0.206

Consistent with H3, there was higher activation in brain regions associated with error processing (the anterior insula and ACC) for prediction disconfirmations than for prediction confirmations. An exploratory whole-brain analysis revealed no additional significant clusters of activation differences (see https://neurovault.org/collections/12268/ for contrast maps).

To assess whether there were neural differences for positive vs. negative disconfirmation and prediction confirmation, as posited by H4, we contrasted activations for positive prediction error (LH), negative prediction error (HL), and confirmation conditions in the ventral striatum and VTA. Figure 6 depicts the locations of the regions of interest and mean BOLD activation (beta estimates) used to test H4, and Table 9 reports the mean activation differences along with inferential statistics.

There was significantly higher BOLD activation for the confirmation condition than the HL (negative prediction error) condition in the right ventral striatum ($t(28) = 2.887$, $p = 0.004$, one-sided). However, inconsistent with H4, the difference in activation between positive (LH) and negative (HL) prediction error conditions failed to reach significance. Similarly, there was no differentiation of activation between these conditions in the VTA. Thus, we observed partial support for H4.

Finally, in parallel with our behavioral hypotheses that posited differences in final ratings based on initial expectations, we performed an analysis of the fMRI data incorporating the change in behavioral ratings between phase 1 and phase 2 for each trial. Trials were categorized according to participants' change in ratings between phase 1 and phase 2. In order to maximize the reliability of the estimate of fMRI activation, we collapsed large ratings changes equal to or greater than 2 in either direction, resulting in response categories for ≤-2, -1, 0, +1, and ≥+2.[5] Consistent with H3, we predicted that activation in regions sensitive to expectation violations tested in H3 (i.e., left and right anterior insula and ACC) would show a U-shape function, with greater activation for large rating changes in either disconfirmation direction. Consistent with H4, we predicted that activation in regions sensitive to negative and positive prediction error (i.e., left and right ventral striatum and VTA) would approximate a linear function, with greater activations for positive shifts in ratings. Figure 7 depicts the fMRI activation for the ROIs tested in H3 (Figure 7 left) and in H4 (Figure 7 right). Visual inspection indicates a roughly U-shaped function in the H3 regions of interest, as we predicted. Although the quadratic contrast failed to reach significance (see Table 10), we did find significant differences between the ≤ -2 and 0 conditions in the left insula ($t(28) = 3.273$, $p = 0.003$), right insula ($t(28) = 3.140$, $p = 0.004$), and right ACC ($t(28)=2.084$, $p=0.046$) and between the ≥ +2 and 0 conditions in the right ACC ($t(27) = 2.349$, $p = 0.026$). Similarly, there appears to be a linear trend, as predicted in the H4 ROIs. Although the linear contrast again failed to reach statistical significance (Table 10), we observed significant differences between the endpoint conditions (≤ -2 and ≥ +2) in the VTA ($t(27) = 2.424$, $p = 0.022$). These results provide additional confirmatory evidence of the patterns anticipated in H3 and H4.

6 Discussion

Adoption and use of information via technology-mediated channels is a core province of the IS discipline; nevertheless, despite their popularity as a platform for technology-mediated knowledge exchange, relatively little is known about the way knowledge seekers evaluate and filter information found on ENP forums. By employing a combined behavioral/NeuroIS approach that integrates concepts from expectation confirmation theory (Oliver, 1980, 2010), prediction error (Schultz, 2016; Schultz & Dickinson, 2000), and prospect theory (Kahneman & Tversky, 1979), this study addresses an important facet of this question by exploring how filtering judgments are influenced when expectations formed on the basis of contextual cues are confirmed or disconfirmed by examination of solution quality. Our results point to several interesting implications for ongoing theory development in this area.

First, although expectation confirmation theory has been applied to understanding use and satisfaction with *information systems*, to our knowledge, this study is the first in the IS domain to examine how expectation confirmation operates in the context of filtering *information itself*, specifically, information that is encountered in increasingly popular online forums. Our results provide theoretical evidence that filtering judgments exhibit both assimilation and contrast patterns that correspond with the predictions of an assimilation-contrast account of expectation confirmation. This result is consistent with other IS research that has explored expectation confirmation in adoption of information *systems* (Brown et al., 2014), but represents a novel finding with respect to the adoption of information itself.

[5] One participant did not have any trials with rating changes ≥+2 and was excluded from direct contrasts involving that condition but was otherwise included in these analyses.

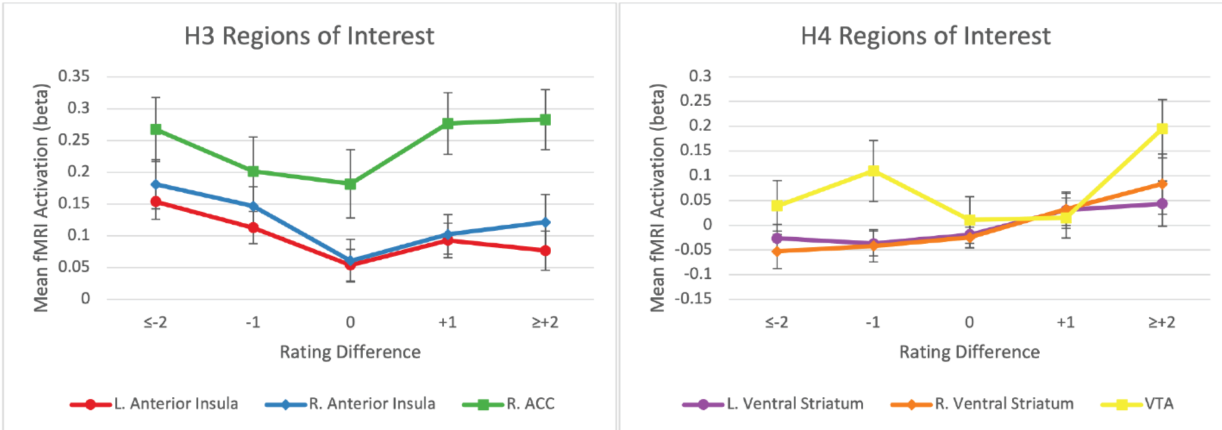


Figure 7. Exploratory Analysis of fMRI Activation as a Function of the Change in Participants' Ratings between Phase 1 and Phase 2 of Each Trial in Regions of Interest Used to Test H3 (left) and H4 (right). Error Bars ±SEM

Table 10. Quadratic and Linear Contrasts of the Activation in the H3 and H4 ROIs as a Function of the Change in Rating between Phase 1 and Phase 2 of Each Trial

Region	Contrast	F	Df1	Df2	Sig.
L Anterior Insula	Quadratic	2.566	1	27	0.121
ACC	Quadratic	3.684	1	27	0.066
R Anterior Insula	Quadratic	4.159	1	27	0.051
L Ventral Striatum	Linear	1.842	1	27	0.186
R Ventral Striatum	Linear	3.054	1	27	0.092
VTA	Linear	1.884	1	27	0.181

Specifically, although some studies in technology-mediated information exchange have emphasized the role of content in information adoption decisions (e.g., Fadel et al., 2009; Sussman & Siegal, 2003), our results show that judgments of solution quality on ENP forums do indeed assimilate to expectations formed on the basis of contextual cues, meaning that more robust content-based evaluation is not immune to influence from contextual cues, even in cases where the evaluator's expertise enables judgment of the solution on its own merits. Moreover, when judgments of solution quality are markedly different from expectations based on contextual cues, the contrast can produce a "slingshot" effect that produces more extreme evaluations than would occur had expectations been confirmed or mildly disconfirmed (Brown et al., 2014). For theory, this implies that the effects of expectation (dis)confirmation on ENP information filtering are likely not monotonic, but rather shift in correspondence to the gap between cue-based expectations and content-based experiences. Ongoing work in this domain should examine further the interplay and boundary conditions between the magnitude of expectation disconfirmation and the associated assimilation/contrast effects that occur as a result.

Another interesting behavioral implication of our results can be derived from the asymmetric effect of positive disconfirmation (unexpected gains) and negative disconfirmation (unexpected losses) in information filtering tasks (H2). Because people consult ENP forums to find solutions to problems, one might expect the identification of an optimal solution to be the primary driver behind information filtering decisions. However, our study provides support for the prospect theory notion that, in ENP information filtering, losses factor more heavily than gains in people's adjustments to their evaluation decisions. Specifically, our results suggest that information seekers are more inclined to change their initial filtering judgments when they believe that doing so avoids the adoption of a *bad* solution than when they believe that it leads to the adoption of a *good* solution. This intriguing result has not yet been demonstrated in the ENP literature but is consistent with predictions of prospect theory (Kahneman & Tversky, 1979) as well as with results of other expectation confirmation research in the IS domain. For example, Brown et al. (2014, p. 749) found that "the negative influence of negative disconfirmation had a stronger impact on user evaluations [of an information system] than the positive influence of positive disconfirmation," leading them to conclude that the positive effect of exceeded expectations is proportionally smaller than that of unmet expectations on system evaluations. Our results suggest that a similar phenomenon occurs for evaluating information itself—people appear, either consciously or subconsciously, to take lesser measures to adopt valid ENP solutions than they do to avoid faulty ones. This result merits further scrutiny and highlights a need for ongoing theoretical development on the interplay of gain seeking and loss avoidance in ENP information filtering tasks.

Additional theoretical implications can be drawn with respect to the neural results of our study. In connection with H3, we find evidence for differential neural indices of confirmation vs. disconfirmation, regardless of the direction (positive or negative) of the confirmation/disconfirmation. Based on prior literature, we hypothesized that there would be greater activation in brain regions associated with error processing, such as the anterior insula and anterior cingulate cortex (ACC), for disconfirmation conditions than for confirmation conditions. Previous neuroscience literature has demonstrated that the ACC and bilateral anterior insula responds to errors, both when the participant is consciously aware and not aware of the error (Klein et al., 2007). Models of reinforcement learning commonly incorporate a "surprise" term that captures the difference between the expected outcome of an event and the actual outcome. Models such as the PRO (predicted response outcome; Alexander & Brown, 2011) propose that the ACC performs a kind of error monitoring by signaling deviations from expectations for both better-than-expected and worse-than-expected outcomes. Our data are consistent with such models and show that neural error detection extends to the domain of ENP information filtering. Specifically, the results of our experiment provide novel evidence that neural mechanisms known to be associated with expectation disconfirmation related to primary reinforcers such as food and water (e.g., D'Ardenne et al., 2008) appear to be similarly implicated in resolving expectation disconfirmation associated with informational cues such as those found on ENP forums. For IS research, our results provide complementary and confirmatory neurobiological evidence of expectation-confirmation processes at work during ENP information filtering. These results highlight the important role of contextual cues in the information filtering processes, and show that expectations based on contextual cues influence subsequent content-based evaluation at the neurological level.

We further hypothesized (H4) that regions preferentially associated with prediction error, namely the ventral striatum and VTA, would show differential responses depending on the direction of the prediction error, whether positive or negative. This hypothesis was based on previous neuroscience literature demonstrating that dopaminergic neurons in the ventral striatum scale their responses according to the prediction error with an increase in firing for greater-than-expected rewards (i.e., positive prediction error) and a decrease in firing for less-than-expected rewards (i.e., negative prediction error). We do show a trend in this direction, with higher fMRI activation for positive prediction errors (LH) than for negative prediction errors (HL); however, this contrast does not reach statistical significance. Negative prediction error did have significantly lower fMRI activation than expected outcomes (confirmation), which is consistent with previous fMRI findings using primary rewards (e.g., D'Ardenne et al., 2008). For IS theory development, our results suggest that the neurocognitive systems that distinguish between expected and unexpected outcomes in an ENP context appear to be similar to those that distinguish between unexpected losses and gains in other domains. In particular, the diminished activation of the right ventral striatum for negative disconfirmation vs. confirmation affirms prior research showing that the ventral striatum is more attuned to processing gains than losses (Taswell et al., 2018). However, the larger activation *difference* between negative disconfirmation vs. confirmation as opposed to positive disconfirmation vs. confirmation suggests that the negatively skewed behavioral adjustments observed in connection with H2 may arise from differently scaled neural responses to positive vs. negative prediction errors. This apparent asymmetry reinforces the idea that information seekers do not respond equivalently to positive vs. negative disconfirmation on ENP forums. Rather, in keeping with prospect theory, our results imply that the neurocognitive functions involved in information filtering might be more sensitive to encountering worse-than-expected solutions than to expected or better-than expected solutions. Further investigation of this possibility presents an area of important inquiry for ongoing behavioral and NeuroIS research.

For practice, the results of our study substantiate the important role that contextual cues play in the filtering process. Both forum designers and ENP knowledge seekers should be aware that expectations formed based on contextual cues may sway later judgments based on solution content. Specifically, our results show that for small perceived discrepancies between indications of contextual cues and content quality, judgments of solution quality are moderated by expectations set by contextual cues; however, large discrepancies seem to produce contrast effects that cause knowledge seekers to become more extreme in their evaluations, *contrary* to the indications of contextual cues. Over time, repeated exposure to such discrepancies could erode confidence in these cues and lead forum users to discount their indications altogether, leaving scrutiny of content as the only viable means of evaluating solution quality and causing users to look elsewhere for platforms that offer less taxing ways of evaluating solution quality. This suggests that forum designers should ensure that contextual cues accurately represent the actual quality of forum solutions. Additionally, to the extent that the filtering is subject to metacognitive control, ENP knowledge seekers should be conscious of the apparent bias in the adjustment of filtering judgments that favor avoiding a bad solution over adopting a good solution. If the trial-and-error cost is relatively low, it may be worthwhile to pay more attention to solutions that appear to be viable for the given problem, even when contextual cues indicate otherwise.

7 Limitations and Conclusion

This study has limitations that should be considered when evaluating its results. First, our experimental design induced a controlled information processing sequence that presented solutions one at a time, with contextual cues first, followed by solution content. Although this ordering was intentional for our research purposes and is supported by prior research (Meservy et al., 2014), filtering patterns on actual forums may differ (e.g., the person could examine the solution content first, followed by the contextual cues). Additionally, although every effort was made to maximize the fidelity of our experimental instrument to actual ENP forums, unavoidable environmental differences remain between a controlled fMRI environment vs. the natural context of ENP filtering, which may affect the generalizability of our results. We selected programming as our experimental context, where we controlled for objectively correct or incorrect answers; however, some ENPs have solution content that is more subjective depending on the context of the individual evaluating the proposed solution. Third, our participant sample was 93% male. Although this is roughly representative of the gender imbalance in the programming domain (Murthy, 2014), it may temper the generalizability of our findings to other ENP forum domains that have broader appeal to women or both genders.

In conclusion, this study is among the first to apply a NeuroIS approach to the domain of information filtering in ENP forums. By integrating diverse theoretical perspectives, our results offer important insights into how expectation confirmation/ disconfirmation based on contextual cues and solution content influences ENP information filtering patterns, both behaviorally and on a neural level. We encourage ongoing research that builds upon and extends the theoretical and practical groundwork laid by this study.

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Appendix A: Experiment Description

The data used in this study were collected using a custom experimental instrument that participants interacted with while in an MRI machine. Figure A1 provides a high-level overview of the steps of the experiment. Participants were experienced software developers and were initially screened to ensure they were eligible to participate in the study. Upon arriving at the MRI facility, participants were provided with the research study consent form and once again screened to ensure participant safety. Participants then watched an overview video that explained the purpose of the experiment, the types of programming problems to be presented, the experimental task procedures (e.g., how to answer questions using a 4-button controller), and safety protocols related to the MRI machine. At this point, researchers answered any questions and reiterated safety procedures related to the scanner.

Participants then proceeded with the main experiment where they were situated in the scanner. A quick localization scan and a seven-minute structural scan were completed so that the participant's brain structure could be co-registered with the functional MRI data. After the structural scan, a task training session was conducted wherein participants viewed and evaluated four different sample solutions to familiarize them with the experimental task. Researchers then answered any questions related to the task before beginning the actual experiment.

During the experiment, participants were shown eight different solutions to six different problems, for a total of 48 different solutions. For each problem, the instrument presented eight different solutions, each consisting of a combination of three cues (expert rating, community rating, and code quality), each with one of two levels (e.g., high quality, low quality). The eight solutions for each problem thus offered a full factorial design with random pairings among the two levels of each factor and random ordering of solutions within each problem. Although we presented and collected data on all 48 solutions, this study is focused on expectation disconfirmation between contextual cues (i.e., expert and community ratings) and content (i.e., code) and only uses data from the 24 solutions (four per problem) where the contextual cues were congruent in their indications. Figure A2 shows a sample solution with a high expert rating, a high community rating, and high code quality.

All solutions for a given problem were presented in a random sequence to reduce cognitive load. To minimize fatigue, the experimental task was split into two question blocks where participants evaluated solutions to three of the problems (24 solutions) during Block 1 and the final three questions during Block 2. Participants were able to rest between blocks. Although solutions were grouped within each problem, the order of problems and solutions within each problem were randomized. Further, other aspects of the experimental instrument were randomized including information related to the expert (name and image) and pairing of code blocks with contextual cues.

Each solution was presented for an interval of up to 30 seconds that was split into two variable-length phases. During phase 1, participants were shown the solution with the code blurred and asked to provide an initial rating based solely on the contextual cues. Participants used the button bar to select how likely they would be to adopt the presented solution on a 5-point Likert scale ranging from unlikely to likely. Once participants selected and locked in their rating, they moved on to phase 2 where the code was unblurred and they could adjust their initial rating based on evaluation of the code. After 30 seconds had passed, a blank screen was presented with a fixation cross for two seconds in between stimuli. As phases were self-terminated when the participant locked in a rating, each phase had a variable length for each solution. On average, participants took 4.7 seconds (*SD* = 2.2 seconds) during phase 1 and 16.5 seconds (*SD* = 6.1 seconds) during phase 2. Figure A3 provides an overview of a sample stimulus block.

In our fMRI individual-level analysis (described in Appendix B), we modeled the two phases as variable-length events. Signal data for any remaining time left in the 30-second block was combined with data captured during the two second interstimulus interval in the model's baseline, thus accomplishing random temporal jitter between trials in the model. This represents a mixed blocked/event-related design (Petersen & Dubis, 2012) which more closely mirrors a participant's experience when seeking information from an online forum.

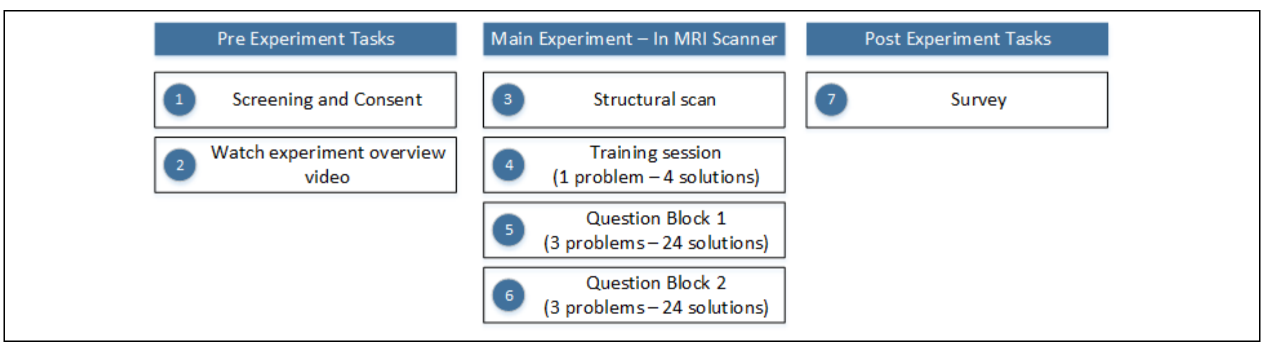

Figure A1. Experiment Overview

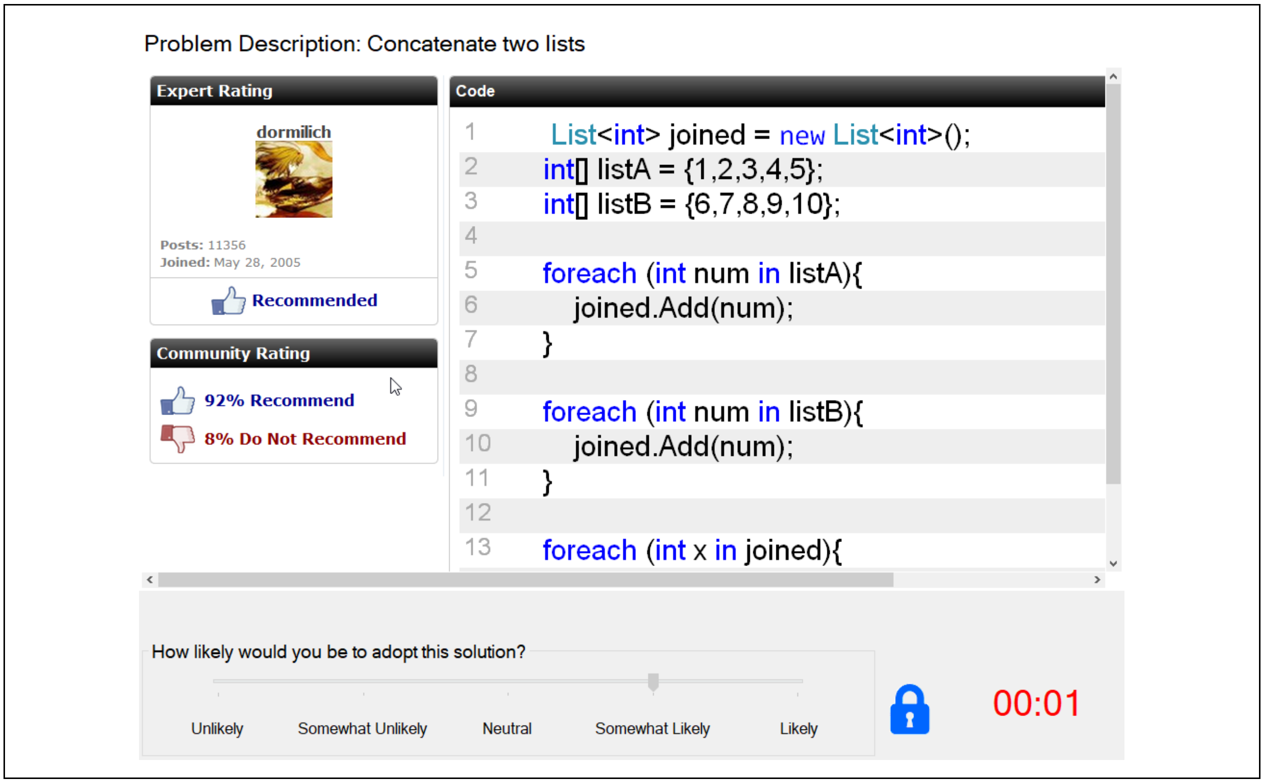

Figure A2. Sample Stimulus Layout for Phase 2

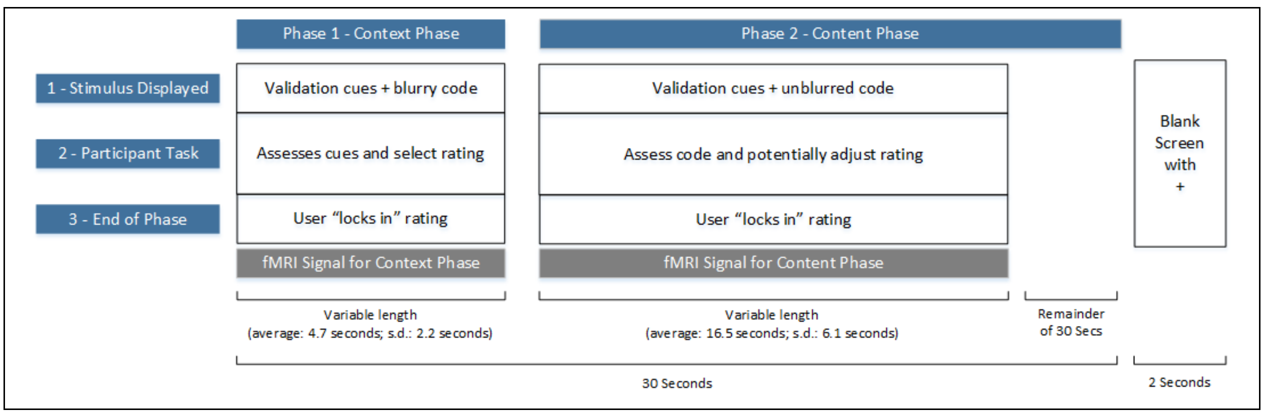

Figure A3. Overview of Each Stimulus Block

Appendix B: MRI Scanning Parameters and Analyses

All MRI data are available from https://openneuro.org/datasets/ds001353 and analysis scripts are available from https://github.com/Kirwanlab/InformationFiltering. MRI scans were acquitted using a 3-Tesla Siemens Tim Trio scanner with 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 = 0.97 × 0.97 × 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. MRI data were analyzed using Analysis of Functional Images (AFNI; version AFNI_18.2.15). MRI preprocessing included estimation of motion correction parameters based on the functional volume (or TR) with the lowest noise levels. Structural scans were also aligned with this functional volume then skull stripped and warped into MNI space using a non-linear diffeomorphic transformation. All motion correction and spatial normalization transformations were concatenated such that functional data were transformed just one time, thus reducing blurring from repeated resampling. Final spatial resolution of the functional data was maintained at 3 × 3 × 3mm. Functional data were scaled by the mean of the signal within each voxel for each run. Functional volumes (or TRs) with large motion events were excluded from the single-subject first-level regression analysis. Coverage masks were created for each subject that excluded voxels with very low EPI signal. These coverage masks were combined with a gray-matter mask in the whole-brain group analysis described below.

Single-subject first-level regression analyses were conducted to fit the ideal hemodynamic response to the neural data for each voxel. The design matrix for the regression model included polynomial regressors to account for scanner drift and low-frequency fluctuations in the signal (7 regressors per run), and regressors for motion for each run (3 translations, 3 rotations, 2 runs). Behavioral regressors coded for phase 2 timepoints for HH, LL, HL, and LH task conditions. Regressors also coded for all phase 1 timepoints and phase 2 timepoints where contextual cues were inconsistent with each other (see footnote 2 in the main text). Both of these classes of conditions were not considered in further analyses. Behavioral regressors were modulated by the time to lock in the final response and convolved with the canonical hemodynamic response. All nuisance regressors (polynomial drift and motion regressors) were included in the model baseline; thus, the baseline (or "0") in the model represents the null hypothesis against which beta-weights were calculated for the active task conditions (see https://afni.nimh.nih.gov/pub/dist/doc/program_help/ 3dDeconvolve.html) and does not represent a true baseline of brain activity. Accordingly, all comparisons in subsequent analyses were made between active task conditions and not against the baseline model. Parameter estimates (i.e., betas) from these individual-level models were not blurred prior to a priori anatomical ROI or whole-brain exploratory analyses.

Regions of interest (ROIs) were defined using meta-analyses in Neurosynth (neurosynth.org) for the search term "prediction error". The Neurosynth algorithm returns two types of maps: *uniformity* test maps, which indicate brain locations that are consistently but non-specifically active in studies associated with the search term, and *association* test maps, which highlight brain locations that are *preferentially* or specifically associated with the search term. Both sets of maps were FDR corrected at 0.01 and further restricted to include just the largest, most reliable clusters. The Uniformity map regions included left and right anterior insula and right anterior cingulate (ACC) cortex in addition to the left and right ventral striatum (see Table B1). The Association map included the left and right striatum and a cluster in the midbrain, presumably the VTA (Table B2). Since ventral striatum appeared in both maps, we focused on the unique clusters when testing H3, which regarded non-specific error processing signals. For both sets of analyses, we performed "whole-ROI" analyses by extracting the mean beta-values from the whole ROI for further analyses. Some software packages (i.e., SPM) use the term "ROI analysis" to refer to voxel-wise analyses within a smaller region of interest with adjusted corrections for multiple comparisons. Since we treated each ROI as a single unit, correction for multiple comparisons across voxels was not necessary for this analysis. Whole-brain exploratory (or "voxel-wise") analyses used two-tailed comparisons between conditions of interest (e.g., positive prediction error vs. negative prediction error). We employed the equitable thresholding and clustering (ETAC) method to control for multiple comparisons (Cox, 2018).

Table B1. Regions of Interest Identified in the Neurosynth Uniformity Test (or nonspecific) Map.

Label	Volume (mm^3)	Center of mass (MNI)		
		X	Y	Z
L ventral striatum	3753	-13	7.8	-6.4
R ventral striatum	3699	13.6	8.7	-3.6
L anterior insula	2916	-33.2	20.9	-2
R anterior insula	2565	35.3	21.6	-2.4
R anterior cingulate	1782	1.9	19.3	46.7

Note: The anterior insula and anterior cingulate regions were used to test H3. L = left; R = right

Table B2. Regions of Interest Identified in the Neurosynth Association Test Map Used to Test H4.

Label	Volume (mm^3)	Center of mass (MNI)		
		X	Y	Z
L ventral striatum	3159	-12	8.2	-8.4
R ventral striatum	2592	13	9.6	-6.4
R ventral tegmental area	405	4.5	-14.3	-22.3

Note: L = left; R = right

Appendix C: Regression Models

Table C1. Mixed Effects Models

	Base model		Model with control variables	
Fixed effects variables	**Estimate**	**SE**	**Estimate**	**SE**
(Intercept)	4.33***	0.09	4.63***	0.51
HL	0.04	0.12	0.04	0.12
LH	-2.79***	0.11	-2.79***	0.11
LL	-2.74***	0.12	-2.74***	0.12
Phase 2	-0.12	0.11	-0.12	0.11
HL * Phase 2	-1.93***	0.15	-1.93***	0.15
LH * Phase 2	1.79***	0.15	1.79***	0.15
LL * Phase 2	0.05	0.15	0.05	0.15
Gender = female			-0.34*	0.16
Age			0	0.01
Education level			-0.04	0.04
Years experience			-0.01	0.02
Programming knowledge			-0.08	0.08
Problem familiarity			0.10*	0.04
Problem difficulty			0.03	0.03
Log likelihood	1996.0		1989.1	
AIC	4014.0		4014.2	
N (ratings)	1,392		1,392	
N (solutions)	48		48	
N (participants)	29		29	

Note: All models included random intercept effects for solution and participant. HH and phase 1 are baseline conditions in the models. **p* < 0.05; ***p* < 0.01; ****p* < 0.001

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