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# Dissecting the Process of Knowledge Filtering in Electronic Networks of Practice

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## Abstract

*Electronic networks of practice (ENPs) have become an important mechanism for knowledge exchange among loosely connected individuals who share common knowledge interests. While prior research has explored factors that influence knowledge contribution in such networks, less is understood about knowledge evaluation. This study examines the process of knowledge filtering in online ENP forums. Drawing from dual process and information search theories, we hypothesize that performance on a knowledge filtering task will be influenced by the constancy and directionality of search patterns employed by knowledge seekers. Hypotheses are tested in an experiment that utilized an eye tracker to record gaze data from professional software developers using an experimental ENP forum. Results provide general support for the hypotheses, showing that higher filtering accuracy is associated with constant evaluation of solution content and intra-attribute (cross-solution) attentional switching. Implications for research and practice are discussed.*

## 1. Introduction

With modern search engines providing access to unprecedented amounts of information, the Internet has become a central venue for knowledge exchange among individuals of all types. Such exchange is particularly common among *electronic networks of practice (ENPs)*, collections of geographically separated individuals who share common interests but are loosely affiliated and communicate via technology-mediated channels. One of the most common tools used by ENPs is the online knowledge forum, a virtual bulletin board where ENP members can post and retrieve knowledge about various problems relevant to network members. For example, a researcher investigating a new statistical technique may use an online forum to post a question to other members in an ENP about the proper application of the technique. The same researcher may also access the forum and supply answers to the questions of other ENP members.

As illustrated by the above example, knowledge exchange through an ENP forum entails both knowledge contribution and knowledge seeking by ENP participants. To-date, research has begun to investigate what motivates individuals to contribute knowledge to an ENP [1, 2]; however, less is understood about the process by which individuals evaluate and ultimately adopt knowledge from ENPs. Due to the open nature of these networks, the quality of knowledge contributions to an ENP forum is rarely regulated or readily apparent to the knowledge seeker. Most searches in ENP forums produce several, potentially competing candidate solutions that may vary in completeness, accuracy, and utility for solving a given problem. Thus, knowledge seekers bear the responsibility of evaluating candidate solutions, filtering out those that do not appear promising, and ultimately deciding which (if any) will suit their needs. Since adopting flawed or inaccurate knowledge can be very costly, there is significant incentive to better understand the process by which knowledge seekers evaluate and filter knowledge contained in online ENP forums.

We have initiated a series of research studies aimed at achieving better theoretical understanding of how individuals evaluate and adopt knowledge encountered on ENP forums. These efforts include examination of both *what* knowledge seekers evaluate on such forums and *how* they go about doing so. We report results of an experiment relating to the former element in forthcoming research [3]. In this study, we focus on the latter component – i.e., the evaluation *process* in which knowledge seekers engage as they filter and evaluate knowledge encountered on an ENP forum. Specifically, our goal is to understand differences in knowledge evaluation processes employed by knowledge seekers and whether these differences ultimately lead to more accurate filtering outcomes (i.e., properly retaining high quality knowledge and filtering out low quality knowledge). The overarching objective of this research stream is to contribute to a more complete theoretical picture of knowledge exchange within electronic networks of practice.

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## 2. Theoretical Background

### 2.1. Knowledge search, filtering, and adoption

Decision theory suggests that when people face a problem that requires further information, they engage in an knowledge seeking process involving three basic stages: search, filtering, and, ultimately, adoption of some knowledge element that is believed to solve the problem [4]. These stages are depicted in Figure 1. During search[1], the individual collects information that she believes is relevant to the problem at hand. In the context of the example cited earlier, the researcher's search may consist of navigating to an online ENP forum and entering search terms to find posts from other network participants that may be relevant to her questions about the new research method. Once the individual has found potentially relevant information, she engages in filtering and evaluation, wherein she examines each knowledge element and determines whether it should be rejected or retained for further consideration. For example, the researcher might examine a number of forum posts relevant to her question and decide which, if any, are worth considering further. The process of filtering and evaluation ultimately leads to a final adoption decision, wherein the person selects one of the available knowledge elements to be applied to solving the problem. Continuing our example, the researcher would decide on a particular post that she believes accurately addresses her question and implement it in her application of the new research method.

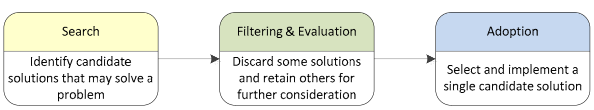


**Figure 1. Stages of knowledge seeking and adoption [3]**

The general process of knowledge seeking and adoption for decision making has an old and rich tradition in cognitive psychology [5-7]. However, it has also experienced a growing interest among information systems (IS) researchers due in part to the increasing role that technology plays in mediating the exchange of such information [8]. A number of IS studies have begun to explore how technology-mediated information is searched and adopted by knowledge seekers. For example, with respect to search, researchers have developed taxonomies of Internet search types [9], explored impacts of the type of task on the search process [10], and examined how and when people stop searching for information online [11]. Another body of literature has explored the adoption of knowledge via technology-mediated channels, including email [12], knowledge repositories [13], and closer-knit communities of practice [14]. Much of this work has relied on dual process models of human cognition such as the elaboration likelihood model (ELM) [15, 16] or the Heuristic Systematic model (HSM) [17, 18] of information processing, which posit that knowledge seekers attend to various types of central and peripheral cues as they determine whether or to adopt technology-mediated knowledge.

While the above-cited literature constitutes an important contribution to our understanding of the knowledge seeking and adoption process, to-date the IS literature has devoted less attention to the *filtering* stage of this process. Studies exploring the knowledge adoption phase [12-14] have focused on the final adoption decision of only one or two knowledge elements that were pre-selected by the researcher or solicited by the knowledge seeker from a known source. While valuable, this approach assumes that the filtering process has already taken place or is superfluous. However, in the context of an ENP forum, the filtering phase is particularly important for several reasons [1, 2]. First, participation in ENPs is self-organizing and voluntary, meaning that "knowledge seekers have no control over who voluntarily responds to their questions, or the helpfulness or relevance of the responses to the current problem at hand" [2, p. 257]. Second, there are few if any restraints on participation in the network, which means that posts to a forum may be made by anyone from experts to novices to even saboteurs. Finally, the asynchronous and geographically distributed nature of the network means that communication between its participants is void of innate social or other non-verbal cues that might ease the filtering process. The combination of these unique ENP characteristics increases the burden on the knowledge seeker who must filter and evaluate multiple solutions from unknown sources in a contextually-sparse environment.

As noted earlier, our focus in this paper is to understand the *process* by which knowledge encountered in an ENP forum is filtered and evaluated. However, doing so requires a theoretical underpinning for understanding what knowledge elements might be encountered on an ENP forum and how they might factor into the filtering decision. Following prior IS literature, we examine this topic through the lens of

[1] The term *search* has been used by some to denote elements of both information collection and evaluation phases. For conceptual and theoretical clarity, we distinguish these phases by using *search* for the former and *filtering and evaluation* for the latter.

dual process theory of information processing, which is now discussed.

### 2.2. Dual process filtering

Theory suggests that knowledge seekers have two competing goals when filtering knowledge en route to a final adoption decision [8, 19]. The first objective is speed: the filtering process should proceed quickly and require as little cognitive effort as possible. The second objective is accuracy: the filtering process should discard low-quality knowledge candidates and retain high-quality candidates for further consideration. A natural trade-off exists between these two objectives: quick, low-effort filtering is likely to compromise accuracy while more deliberate filtering has greater time and effort requirements. This tradeoff coincides with the core tenet of dual process theory of information processing [15, 18]. Dual process theory suggests that information processing occurs along two primary routes: central and peripheral. Central route processing involves deliberate evaluation of the knowledge content itself. Because central processing requires assessment of the knowledge on its own merits, it typically requires more time and effort. In contrast, peripheral processing relies on the interpretation of various peripheral cues surrounding the knowledge. These cues may or may not accurately reflect the quality of the knowledge in question, but are readily available for quick evaluation. According to dual process theory, the more dominant route in a given situation will depend on the expertise and motivation of the knowledge seeker. If motivation and expertise are high, the person will rely more on central route processing, as accuracy is paramount and the person is capable of evaluating the information on its own merits. If motivation and expertise are low, the person is more likely to rely on peripheral route processing, which requires less time and fewer cognitive resources.

How might central and peripheral processing occur in the context of an ENP forum? Central processing, by definition, would require that the knowledge seeker analyze the content of a given forum posting and decide whether it should receive further consideration. Peripheral processing, on the other hand, would rely on surrounding peripheral cues. In ENP forums, such cues commonly include indicators of contributor expertise or external validation of a post by one or more other ENP participants. These cues may or may not accurately reflect the quality of a given post, but can be quickly evaluated as surrogates for knowledge quality. In short, evaluating the content and peripheral cues for multiple potential forum posts constitutes a multi-alternative, multi-attribute filtering task that must be performed by the ENP knowledge seeker.

Theory suggests that both central and peripheral processing are involved in most information evaluation activities and that individuals can switch between them in a given evaluation task [20]. However, exactly how different switching patterns affect filtering accuracy remains unclear. It seems possible, for example, that an ENP knowledge seeker who examines the *content* of each available forum post on a particular topic before considering the peripheral cues surrounding each post might filter the information differently than someone who considers all aspects of one post (content and peripheral cues) before moving to the next. In the following section, we draw on theory in information search for decision making to develop hypotheses regarding how different filtering processes affect the accuracy of the filtering task.

## 3. Hypothesis Development

Literature on information search for decision making suggests two primary dimensions that characterize information evaluation patterns in multi-alternative, multi-attribute filtering tasks [5, 6]. The first dimension concerns the constancy with which the knowledge seeker evaluates the attributes of each solution alternative. To be considered constant, the person should examine the same attributes of each alternative in the filtering process. For example, a person presented with multiple possible solutions on an ENP forum might examine two of the three available attributes (e.g., the solution content and the source expertise) for each solution alternative. Importantly, constancy does not necessarily imply *completeness*; that is, a person does not need to examine *all* of the available attributes, only the *same* attributes across each alternative to be considered constant [5]. Because a constant evaluation pattern implies that the evaluator is comprehensively considering all relevant aspects of each solution alternative, it is suggestive of a *compensatory* evaluation strategy wherein the attribute values of a given solution alternative are comprehensively considered, aggregated, and weighed against the comparative score of another solution alternative. Compensatory evaluation strategies typically require more time and cognitive resources as they require the individual to carefully balance the combination of attributes of one alternative against that of the other alternatives [7]. Consequently, compensatory strategies are often employed when accuracy is important and the individual has the capacity to process the all the relevant information. In contrast, a variable (inconstant) evaluation strategy is characterized by inconsistent examination of the attributes of each alternative. This is usually taken to denote a *non-compensatory* evaluation strategy in which the value for all solution alternatives on a single attribute (or set of attributes) may qualify or disqualify them for further consideration [6]. Congruent with the dual process concept of peripheral route processing, non-compensatory evaluation strategies are typically employed when quick evaluation is paramount and/or when the person lacks the inclination or capability to thoroughly process all the information at hand. For example, in the present context, a knowledge seeker might use a non-compensatory strategy by screening posted alternatives by whether or not they have been validated by a third party, a common peripheral cue in ENP forums. While such a strategy is beneficial for speedy filtering, it is not likely to be as accurate as careful consideration and comparison of all solution attributes. This leads to the following hypothesis:

*H1: In an ENP forum, a predominately constant (compensatory) evaluation pattern will result in greater filtering accuracy than a predominately variable (non-compensatory) evaluation pattern.*

The second dimension of information evaluation patterns concerns the directionality of the search, or the relative frequency of attentional switches between the same attribute of different solution alternatives (termed intra-attribute switching) versus switches between different attributes within the same solution (inter-attribute switching) [5, 8]. Citing the example offered in the previous section, the first individual employs an intra-attribute evaluation strategy while the second employs an inter-attribute strategy. Directionality is a commonly measured characteristic in information-based decision-making literature [7]; however, because most studies have focused on preferential decision tasks, there has been less theorization about how directionality alone influences filtering accuracy in a normative task.

In context of an ENP forum, we hypothesize that intra-attribute search patterns (characterized by focusing on the same attribute across different solutions) will lead to more accurate filtering decisions, particularly an intra-attribute pattern that focuses on the *content* of the solution alternative being considered. The logic behind this hypothesis derives from dual process theory, which holds that systematic (central) processing of the information content itself, though more resource-intensive, usually produces more accurate assessment of objective information quality than does peripheral processing [15, 17]. Peripheral cues, while convenient for quick processing, are often superficial and may be misleading, particularly in the open context of an ENP forum discussed earlier. Thus, if knowledge seekers interrupt their analysis of solution content by alternating their attention to its peripheral cues (inter-attribute switching), their judgments of its objective quality are more likely to be swayed by the potentially unreliable influence of these cues. Moreover, frequent inter-attribute switching among potentially contrasting cues of the same solution (e.g., high source expertise but lack of validation by others) can increase cognitive burden [21], and may obfuscate the evaluation process by interfering with the ability to isolate qualitative differences between the solutions themselves. In contrast, the individual who systematically compares the content of each solution (central-route, intra-attribute processing) should be more likely to properly discern high and low-quality solutions. Thus, we hypothesize that:

*H2: In an ENP forum, a predominately intra-attribute evaluation pattern that focuses on the solution content will result in greater filtering accuracy than a predominately inter-attribute evaluation pattern.*

These two dimensions of filtering patterns may be placed on a quadrant that characterizes an individual's overall evaluation pattern. Such a quadrant is shown in Table 1. Taken together, the combinations of constancy and directionality characterize four prototypical information evaluation models identified in the decision-making literature [5, 7, 22]: additive, additive difference, conjunctive, and elimination-by-aspects. In the additive model (constant, inter-attribute), scores are assigned to each attribute within an alternative and added together. Each alternative is then evaluated holistically in relation to other alternatives. The additive difference model (constant, intra-attribute) works in a similar fashion, except that single attributes are compared across alternatives rather than comparing different attributes within the same alternative. In the conjunctive model (variable, inter-attribute) a threshold value is assigned to all attributes and each alternative is evaluated holistically until one that satisfies each threshold is found. Finally, in the elimination-by-aspects model (variable, intra-attribute) attributes are examined consecutively across alternatives, and any alternative not meeting a minimum threshold on each attribute is eliminated from further consideration.

**Table 1. Filtering patterns quadrant**

| | | Directionality | |
|---|---|---|---|
| | | **Inter-attribute switching** | **Intra-attribute switching** |
| **Constancy** | **Constant (same # of attribs evaluated across all solutions)** | Individuals look at all attributes of the first solution, then move to the second solution and look at all attributes until all solutions have been considered; e.g., Additive model | Individuals look at one attribute across all solutions, then look at the second attribute across all solutions; all attributes for all solutions are evaluated; e.g., Additive difference model |
| | **Variable (different # of attribs evaluated across all solutions)** | Individuals look at all attributes for a single solution; select first solution that satisfies all attribute thresholds; e.g., Conjunctive model | Look at one attribute across all solutions and eliminate from consideration any solution that doesn't satisfy the threshold for that attribute; e.g., Elimination by aspects model |

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# 4. Method

The data for this investigation was collected from a field experiment in which professional software developers were asked to evaluate eight candidate solutions to an array sorting problem in an experimental ENP forum. Four of the candidate solutions presented would actually solve the array sorting problem if implemented while the other four would not. Participants ranked the candidate solutions in the order that they would use them to solve the array sorting problem. The array sorting task was selected because it was sufficiently difficult to motivate an online search for a plausible candidate solution [3].

Data were collected by two primary means: 1) an instrument that utilized an eye tracker designed to capture participants' gaze during evaluation and 2) an online survey administered after participants completed the evaluation task. Analysis of this data in a prior study [3] focused on the moderating role of elaboration and the relative impact of peripheral cues in guiding participants' filtering. In the analysis presented here, we delve more deeply into the filtering stage of knowledge evaluation by examining the actual process by which participants compared candidate solutions. This study uses only the objective data captured by the eye tracker and other objective content recorded by the experimental instrument (e.g., ranking data). A full report of the method and data is reported in [3]; however, we provide a summary of the method here to assist in understanding the data used to test our hypotheses.

## 4.1 Participants

The dataset contained responses from 62 professional software developers from four organizations: 1) a large manufacturer of electronic, mechanical, and utility products, 2) a premier financial services company, 3) a municipal government, and 4) the IT department of a research university. All participants had at least one year of experience and held job titles of developer, senior developer/project lead, tester, or manager. The participants' mean age was 43.8 and 36 percent were female.

## 4.2 Filtering Task

Each candidate solution had a unique combination of objective content quality (high versus low), an indication of the contributor's expertise level (high versus low), and an indication of whether the solution had been validated (accepted versus not validated). There were a total of four candidate solutions that were objectively better than the other candidate solutions. If used, the high quality candidate solutions would correctly sort a given array. The candidate solutions low in content quality had serious omissions, syntax errors, and logic errors. To control for ordering effects, [23], the position of each candidate solution was randomly determined. In addition, each of the eight candidate solutions that was presented to each participant was randomly assembled out of the three components (content, expertise, validation). A sample solution with high expertise and no validation is presented in Figure 2.

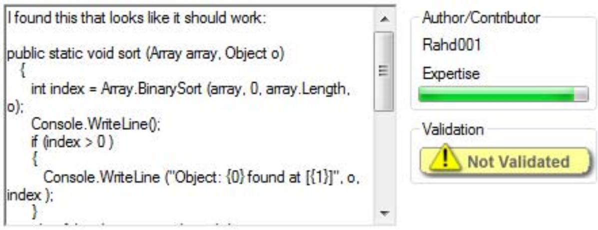


**Figure 2. Sample solution with high expertise and no validation**

### 4.3 Measurement

Capture of participants' gaze was accomplished via a custom application that utilized the Tobii T60 eye tracker and Tobii Studio software. The custom application used the raw coordinates of the participants' gaze to capture the candidate solution and the solution component (content, contributor expertise, validation) that each participant was observing throughout the experiment. The gaze data from each participant was then summarized on the basis of inter-attribute and intra-attribute switching. A participant engaged in inter-attribute switching if she shifted her attention from one attribute to another attribute within the same solution. A participant engaged in intra-attribute switching if she shifted her attention from an attribute in one solution to the same attribute in another solution. Consistent with prior research [5, 22] we calculated a *directionality* ratio of intra-attribute switching compared to inter-attribute switching using the following formula for each participant:

$$\frac{\#\ of\ IntraAttribute\ Switches - \#\ of\ InterAttribute\ Switches}{\#\ of\ IntraAttribute\ Switches + \#\ of\ InterAttribute\ Switches}$$

A value of 1 for this ratio indicates a completely intra-attribute strategy whereas a value of -1 indicates that only inter-attribute switching occurred.

The constancy of attributes consulted during filtering was captured by calculating the standard deviation of the normalized gaze duration for each of the solution components. To accomplish this, each individual's gaze duration was first normalized for each of the three attribute types (i.e., content, contributor expertise, and validation) across all candidate solutions. Normalization of gaze duration was performed to enable comparison of gaze data across all participants for a given performance level. After the duration was normalized across all solutions for a given attribute and participant, the standard deviation was calculated for each attribute. Thus, each participant had a constancy score calculated for all three attribute types. Low standard deviations reflected a more constant search strategy in consulting the respective content, expertise, and validation of candidate solutions, while high standard deviations indicated that a participant demonstrated high variability. Z-scores were then calculated for each constancy score in order to determine the relative positioning of each participant compared to the whole. For ease of interpretation, the score was negated (multiplied by -1) so that a larger score would indicate greater constancy (and less variability).

Finally, a performance index measuring filtering accuracy was created by evaluating the relative ranking of the high- and low-quality solutions. The index was calculated by multiplying the inverse rank of a candidate solution by 1 if the solution content was high quality or by 0 if the solution content was low quality. This was done for each ranked solution. For example if the second ranked solution was high quality, that component of the performance index would be given a value of 7 (i.e., (9-2)*1). These components were then summed to provide an overall performance index for a particular participant. Thus, participants received the highest performance scores if all four high quality solutions were ranked in the top four positions. Participants were further categorized as high, medium or low performers based on quartiles of the performance index, with high performers in the first quartile (17 participants), medium performers in the second and third quartiles (22 participants), and low performers in the fourth quartile (23 participants).

## 5. Results

Hypothesis 1 asserted that a predominantly constant evaluation pattern would result in greater filtering accuracy. Descriptive statistics were calculated for constancy scores and organized by performance level. Table 2 contains averages and standard deviations and Figure 3 visually depicts the averages.

**Table 2. Average standardized constancy scores and standard deviations by performance level**

| Attribute Type | High Performers | Medium Performers | Low Performers |
|---|---|---|---|
| **Expertise** | -0.505 (1.18) | 0.126 (0.98) | 0.253 (0.74) |
| **Validation** | -0.579 (1.18) | 0.175 (0.96) | 0.260 (0.71) |
| **Content** | 0.279 (0.64) | -0.067 (1.17) | -0.142 (1.04) |

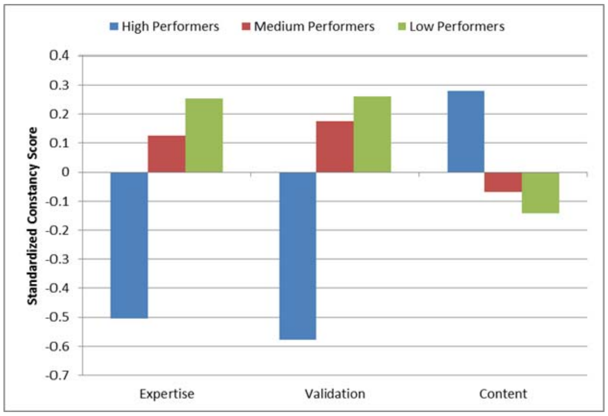


**Figure 3. Standardized constancy scores by attribute type and performance level**

The first hypothesis was tested using a 3 (performance level: high performers, medium performers, low performers) × 3 (attribute: content, source expertise, validation) mixed-model repeated measures design with attribute type as the repeated measure. The standardized constancy score of each attribute was the dependent variable.

Before examining within-subjects effects, the data were first checked for violations of the sphericity assumption. Sphericity violations were found, Mauchly's W = .847, $\chi 2(2, N = 62) = 9.620$, $p = .008$. Therefore, we use the Huynh–Feldt method to adjust our degrees of freedom [24].

The results show there were no significant main effects. However, the interaction between attribute type and performance level was significant, $F(3.687, 108.759) = 3.865$, $p = .007$. From Figure 3 the interaction between attribute types and performance level seemed to be driven by the difference between attribute types for high performers. To further understand the significant interaction between attribute types and performance levels, we conducted a paired *t*-test analysis for each attribute type combination (e.g., validation-vs-content) for each performance level. Table 3 shows that for high performers the amount of constancy is significantly different. None of the other *t*-tests for other performance levels was significant.

**Table 3. Comparison of standardized constancy scores by performance level**

| Performance Level | Attribute Comparison | Stats |
|---|---|---|
| High Performers | Expertise-Content | t(16)=-2.558; p = 0.021 |
| | Validation-Content | t(16)=-3.682; p = 0.002 |

Hypothesis 2 posited that a predominately intra-attribute evaluation that focuses on content would yield higher levels of performance. Descriptive statistics for intra-attribute switches, inter-attribute switches, and the directionality ratio for each of the performance levels are listed in Table 4. Figure 4 visually depicts the directionality ratio for all performance levels.

**Table 4. Descriptive statistics for Hypothesis 2**

| Performance Level | Average Intra-Attribute Switches | Average Inter-Attribute Switches | Directionality Ratio[2] |
|---|---|---|---|
| High Performers | 204.3 (241.0) | 29.6 (12.5) | 0.66 (0.17) |
| Medium Performers | 154.3 (212.2) | 43.4 (32.4) | 0.40 (0.22) |
| Low Performers | 101.0 (85.5) | 34.9 (17.8) | 0.37 (0.28) |

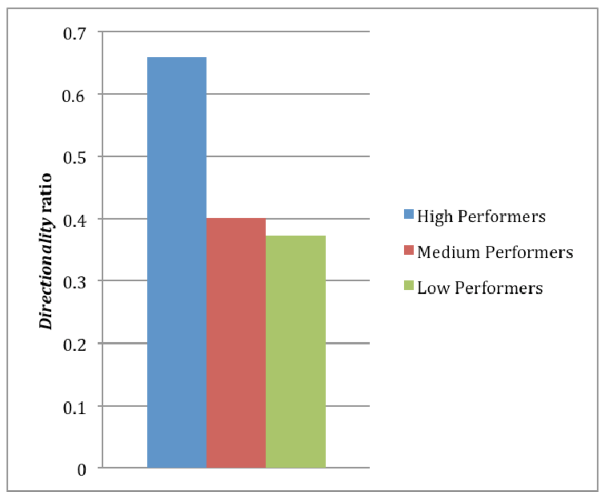


**Figure 4. Directionality ratios for varying levels of performance**

A one-way ANOVA was used to test Hypothesis 2. The directionality ratio differed significantly across the three performance levels, $F(2, 59) = 8.505$, $p = .001$. To fully comprehend the nature of this effect we ran two additional independent samples *t*-test comparing high performers' directionality ratio to other performance levels. High performers were significantly higher than low performers, t(38)=3.752; p = 0.001,

[2] The directionality ratio is computed on a per-participant basis. The intra-attribute switch and inter-attribute switch means listed in the table are calculated across all participants.

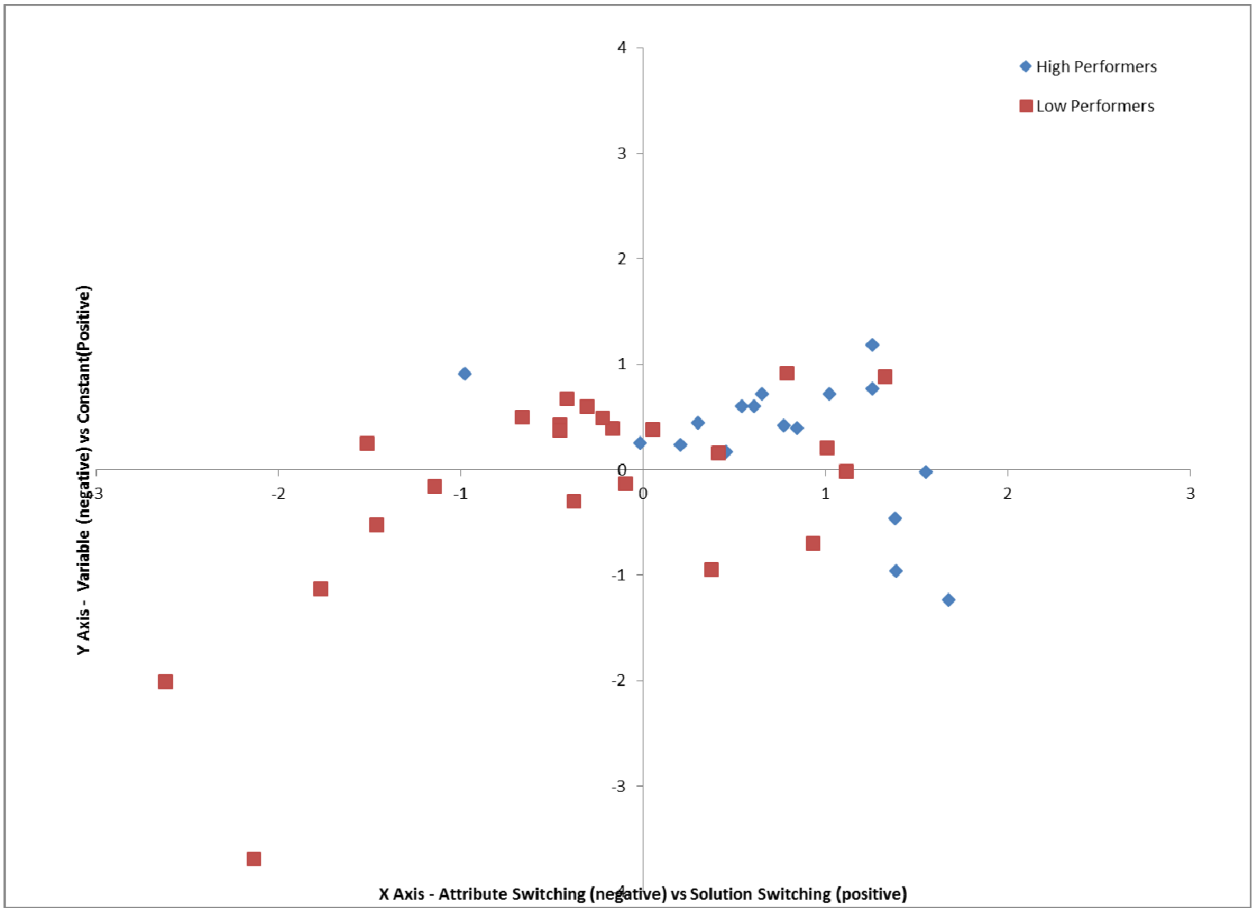


**Figure 5. Overall search pattern by participant for high and low performers**

and medium performers, $t(37)=3.93$; $p < 0.001$. These results support H2.

Combining the two dimensions theorized in H1 and H2, we can roughly characterize the overall search pattern for each participant. Figure 5 shows this information in regards to solution content. As evidenced by this figure, high performers tended to be more constant and engaged predominantly in intra-attribute switching (similar to the additive difference model) while low performers seemed to be scattered across all four quadrants.

## 6. Discussion and Conclusion

The objective of this study was to examine knowledge evaluation patterns in electronic networks of practice, and understand how differences in these patterns related to filtering accuracy in a multi-alternative, multi-attribute decision problems. Drawing from literature on information search for decision making [5, 7, 22] we classified filtering patterns by constancy (i.e., constant vs. variable) and by directionality (intra-attribute vs. inter-attribute). Based on reasoning rooted in this literature and in dual process theories, we hypothesized that accuracy in the filtering task would be higher when search patterns employed more constant evaluation of attributes across alternatives and more intra-attribute vs. inter-attribute attentional switching.

The results of our analysis provide general support for our hypotheses and offer several implications for both research and practice. With respect to H1, we found that constancy in evaluating different solution attributes was related to performance, but not in the same way for all attributes. Specifically, high performers engaged in much more constant analysis of the *content* across all solutions, but did not give equal attention to peripheral cues across all solutions. In contrast, low performers were more constant in their analysis of peripheral cues, and less constant with respect to solution content. Viewing these results through the lens of dual process theory offers interesting insights that extend prior literature on information search for decision making. The pattern exhibited by high performers indicates that peripheral cues received attention for some solutions, but not for others, indicating that these participants may have recognized the potential unreliability of these cues and abandoned them in favor of a more thorough (constant) evaluation of the content of each solution. Stated in terms of dual process theory, high performers seemed to rely more steadily on central route processing (analyzing the content of the solution itself), and only transitorily on peripheral route processing. Thus, consistent with predictions of dual process theory, high performers were better able to accurately distinguish the actual quality of each solution. The implication of this result is that constant (or compensatory) evaluation of attributes alone does not necessarily lead to better filtering outcomes in contexts such as ENP forums where some attributes are peripheral and are of questionable diagnosticity; rather, filtering accuracy seems to depend on whether constancy coincides with central processing of the actual content of a posted solution.

With regard to H2, our results supported the hypothesis that increased intra-attribute switching based on the solution content (as opposed to peripheral cues) would be associated with higher filtering accuracy. This means that high performers tended to move from the content of one solution to the content of another solution, rather than switching between peripheral cues and content within a solution. Again, this pattern suggests that high performers may have recognized the fallibility of the peripheral cues and committed their attention to direct comparisons of the content of each solution. Low performers, by contrast, seemed to engage in more inter-attribute (e.g., within-solution) switching, which may have hindered their ability to objectively compare the content quality of each solution. As with H1, this result highlights the utility of integrating dual process concepts with the dimensions of evaluation patterns studied herein and in previous information-based decision-making literature [e.g., 5, 22]. In particular, our results suggest that that the effect of evaluation directionality on performance may be contingent on the type of attributes (central vs. peripheral) upon which this switching occurs.

This research also carries implications for ENP participants who use forums sponsored by these networks as a knowledge source. Knowledge seekers should be aware that some information evaluation patterns might lead to filtering decisions that are less accurate than others. To the extent that knowledge seekers can consciously alter their evaluation behaviors, our results suggest that a constant comparison of the content of ENP forum posts is more likely to result in accurate filtering decisions. Diverting attention to peripheral cues, particularly those that may be of low diagnosticity, might impair the one's ability to objectively compare the content quality of the each solution.

Finally, this study has limitations that should be considered. As with any experimental research, the external validity of our results may be tempered by the experimental context or artifacts used in our study. Although we took explicit steps to maximize the internal and external validity by using participants who were actual programmers, measuring filtering behaviors using an eye tracking device, and completely randomizing the presentation and combinations of all treatment levels to avoid ordering effects, it is possible that the pattern of results we observed here differs somewhat from ENP forum knowledge evaluation in the field. In addition, different results might be observed in alternative scenarios with more or less alternative/attribute combinations or decision problems that involve higher stakes, such as evaluating alternative surgical procedures or long-term investment strategies. We encourage future research to explore these issues and further test the boundary conditions of the pattern of results observed herein.

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