Influence Of User Expertise, Task Complexity And Knowledge Management Support On Knowledge Seeking Strategy And Task Performance

Hui-Min Lai
Department of Information Management, Chienkuo Technology University, Changhua, Taiwan, R.O.C., hmin@cc.ctu.edu.tw

Shin-Yuan Hung
Department of Information Management, National Chung Cheng University, Chia-Yi, Taiwan, R.O.C., syhung@mis.ccu.edu.tw

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INFLUENCE OF USER EXPERTISE, TASK COMPLEXITY AND KNOWLEDGE MANAGEMENT SUPPORT ON KNOWLEDGE SEEKING STRATEGY AND TASK PERFORMANCE

Hui-Min Lai, Department of Information Management, Chienkuo Technology University, Changhua, Taiwan, R.O.C., hmin@cc.ctu.edu.tw
Shin-Yuan Hung, Department of Information Management, National Chung Cheng University, Chia-Yi, Taiwan, R.O.C., syhung@mis.ccu.edu.tw

Abstract

Knowledge management systems (KMSs) have become increasingly popular as knowledge-seeking tools in many organizations, but little is known about how people search for knowledge from the KMS. The results of a field experiment indicated that (1) the interaction between user expertise and task complexity affects the user’s adoption of ask-directed search and browsing strategies; (2) when a user’s perceived knowledge content quality is high, the interaction between user expertise and task complexity affects the user’s adoption of ask-directed search and browsing strategies; (3) when a user’s perceived KMS quality is high, the interaction between user expertise and task complexity affects the user’s adoption of ask-directed search and browsing strategies; and (4) task completion time and task quality are associated with the user’s adoption of ask-directed search strategies; user satisfaction is associated with the user’s adoption of ask-directed search and browsing strategies. Finally, theoretical and practical implications from the findings are provided.

Keywords: Knowledge-seeking Strategies, Knowledge Management Systems, User Expertise, Task Complexity, Field Experiment
1 INTRODUCTION

Knowledge seeking is a crucial activity in problem-solving processes. Knowledge management systems (KMSs) have become increasingly popular as knowledge-seeking tools in many organizations, but little is known about how people search for knowledge from the KMS. With the large amount of knowledge stored in the KMS and the variety of means to seek knowledge, there is an even more need to understand why some seekers are more successful than others in locating the knowledge they need. Cognitive science research reveals that locating appropriate information requires a variety of skills, such as the ability to use tools, employ search techniques, organize a search, and execute the search (Carroll, 1999).

This study integrates the cognitive science perspective on the difference between experts and novices with knowledge management literature and examines how user expertise (experts versus novices), task complexity (low versus high), and knowledge management support (users’ perceived knowledge content quality and users’ perceived KMS quality) influence the adoption of knowledge-seeking strategies (ask-directed search and browsing strategies) and task performance (task completion time, task quality, and user satisfaction). Understanding users’ knowledge-seeking strategies and task performance and then incorporating such understanding into system design is critical to constructing usable KMSs and interfaces.

2 THEORETICAL BACKGROUND

2.1 Knowledge seeking in KMSs

Previous research on knowledge-seeking behaviors in KMSs has focused mostly on individual motivation, which might enhance or undermine an individual’s knowledge-seeking behavior through a KMS. For instance, Phang et al. (2009) investigated two activities (i.e., knowledge seeking and contribution) by participants in online communities. They adopted a socio-technical perspective on online communities to explore the effects of usability and sociability, which in turn influence knowledge seeking and contribution. Specifically, when individuals sought knowledge, both ease of use and system reliability were deemed more important to usability and moderator perception was considered more important to sociability. On the other hand, when individuals contributed knowledge, they deemed tracking fulfillment to be more important to usability and social interactivity to be more important to sociability. He et al. (2009) drew upon the extant literature on trust and information technology adoption and examined the relationships between knowledge seekers’ trust in the community of KMS users, their perceptions of the system (perceived usefulness and perceived seeking efforts), and their intention to continue to use the KMS. The results reveal that trust in the community of KMS users does not directly affect employees’ intentions to continue seeking knowledge; rather, the effect occurs indirectly through a mediated effect of the perceived usefulness of the KMS. They also found that trust seems to be a stronger determinant of perceived usefulness than of perceived seeking efforts. He and Wei (2009) examined the differences among the factors driving continued knowledge-seeking and contribution behaviors. The results show that knowledge workers go to a KMS to contribute knowledge for reasons such as social relationships, enjoyment in helping others, management support, and consideration of cost associated with contributing behavior rather than for reasons such as image, reciprocity, or organizational reward. In the seeking context, knowledge workers show continued usage behavior based on the utility of the system, social relationships, and seeking effort involved. Surprisingly, however, they are not motivated by knowledge growth, organizational rewards, or management support. Bock et al. (2006) used the social exchange theory to identify the costs and benefits of knowledge seeking. Based on the social capital theory, they identified collaborative norms that play a moderating role in the influence of other antecedents on knowledge seeking via electronic knowledge repositories (EKRs). The results indicate
that collaborative norms have positive impact on individuals’ usage of the EKR s for knowledge seeking, both directly and by reducing the negative effect on seeking of future obligation. In contrast, collaborative norms can undermine the positive impact of perceived usefulness on knowledge-seeking behavior. In addition, seeker knowledge growth, resource-facilitating conditions, and self-efficacy are positively related to EKR usage for knowledge seeking. Kankanhalli et al. (2005) drew from the theories of planned behavior and task-technology fit to understand the potential antecedent factors to EKR usage for knowledge seeking. Their results reveal that perceived output quality directly affects EKR usage for knowledge seeking. Further, resource availability affects EKR usage for knowledge seeking, particularly when task tacitness is low, and incentives affect EKR usage, particularly when task interdependence is high.

In summary, research into knowledge seeking has yielded extensive explanations regarding the motivations of individuals in using KMSs to seek knowledge, but studies on the strategies adopted by people seeking knowledge from KMSs are few.

2.2 Seeking strategy

A strategy is an “approach that an information seeker takes to a problem” (Marchionini, 1995). Marchionini (1995) pointed out that there are two strategies for searching in an electronic environment: analytical and browsing strategies. Formal, systematic, batch-oriented, well-planned, and goal-driven strategies are analytical strategies. Opportunistic, informal, heuristic, data-driven, and interactive strategies are browsing strategies. Vandenbosch and Higgins (1996) indicated that information retrieval or acquisition strategy in the executive information system can be divided into either scanning or focused search. A scanning strategy is used “when people browse through information without a particular problem to solve or question to answer” (p. 202). A focused search strategy is used “when people are looking for specific information” (p. 202). Hertzum and Frøkjær (1996) pointed to browsing and querying as two retrieval processes in text retrieval systems. Browsing allows users to quickly evaluate a large amount of information and to determine which is useful. In querying, a user can enter the query terms into the input field and see references to the texts that match the query. Rowley (2000) indicated that online product search strategies can be distinguished into either browsing or directed search. Browsing indicates that people have no particular goal in mind or only a vague notion of what they want to find. Directed search assumes that people know, at least generally, what they are looking for and have a goal in mind that can direct their search. Bhalotia et al. (2002) found that users’ information retrieval on relational databases can be divided into keyword searching and browsing. In keyword searching, users use a keyword-based search or data and schema browsing. Keyword searching uses proximity-based ranking based on foreign key links and other types of links to match data (tokens appearing in any textual attribute) and metadata (including column or relation name). By browsing, a system can be used to automatically generate browsable views of database relations. Nachmias and Gilad (2002) examined searching information on the WWW and proposed that online search strategies can be categorized into search engine strategies, browsing strategies, and direct access strategies. Users adopt the search engine strategy for direct single-keyword searches, wide search definitions, use of general knowledge, computer convention, and Boolean and complex searches. The direct access strategy employs direct typing, whereas the browsing strategy involves accessing a directory or a specific portal. Huang (2003) pointed out that the information retrieval strategy of hypermedia systems include index searching and browsing. Index searching, also known as querying, “involves using an indexing system in which users enter relevant keywords to locate information” (p. 191). Browsing means users “navigate a database by following links from one item to another” (p. 191).

In this study, knowledge seeking refers to an individual’s knowledge-seeking strategy in a KMS, which includes ask-directed search and browsing. Ask-directed search strategies means users are goal driven and can narrow down their search scope with certain targets by using keyword search, and browsing strategies means user are data driven that can either browse at their pleasure or scan large quantities of information for their information needs by using categorized browsing functions.
<table>
<thead>
<tr>
<th>Study</th>
<th>Research context</th>
<th>Seeking strategy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Marchionini (1995)</td>
<td>Electronic environment</td>
<td>• Analytical • Browsing</td>
</tr>
<tr>
<td>Vandenbosch and Higgins</td>
<td>Executive information system</td>
<td>• Focused search • Scanning</td>
</tr>
<tr>
<td>(1996)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hertzum and Frøkjær (1996)</td>
<td>Online documentation</td>
<td>• Querying • Browsing</td>
</tr>
<tr>
<td>Rowley (2000)</td>
<td>Online documentation</td>
<td>• Directed search • Browsing</td>
</tr>
<tr>
<td>Bhalotia et al. (2002)</td>
<td>Relational databases</td>
<td>• Keyword search • Browsing</td>
</tr>
<tr>
<td>Nachmias and Gilad (2002)</td>
<td>World Wide Web</td>
<td>• Search engine • Direct access • Browsing</td>
</tr>
<tr>
<td>Huang (2003)</td>
<td>Hypermedia systems</td>
<td>• Index searching • Browsing</td>
</tr>
<tr>
<td>This study</td>
<td>Knowledge management system</td>
<td>• Ask-directed search • Browsing</td>
</tr>
</tbody>
</table>

Table 1. The seeking strategies studied in prior research

3 RESEARCH MODEL AND HYPOTHESES

3.1 Research Model

This study classifies the impact factors of seeking strategy into internal variables and external variables. External variables are independent from the seeker, which includes the task complexity and knowledge management support. Internal variables are related to the seeker, including the user expertise. This study is being conducted on the ground of the McGrath’s (1964) input-process-output model.

![Research model](image)

Figure 1. Research model
3.2  Research Hypotheses

3.2.1  Influence of user expertise and task complexity on the adoption of knowledge-seeking strategies

Choosing one strategy usually reflects a trade-off between effort and accuracy (Payne et al., 1993). The basic premise is that people tend to choose a strategy that produces a high level of accuracy yet requires little effort (Payne et al., 1993). The cognitive structure of experts involves many highly-interrelated knowledge units organized according to the similarity of the fundamental structures in each unit, while the schema of novices involve relatively few knowledge units that are not interrelated with each other and so are organized by surface similarity (Sternberg, 2003). As Barrick and Spilker (2003) suggested, experts should use more directed, less sequential search strategies, while novices should use more sequential and less-directed search strategies.

However, when tasks become more complex, the number of information-processing steps increases to reflect the increased interdependency between the information-processing steps (Wood, 1986) and the cognitive effort increases accordingly. People tend to choose a sophisticated and therefore more effort-demanding strategy when they are seeking an accurate result (Kuo et al., 2004). These findings may contradict and be inconsistent with the effort-accuracy trade-off model proposed by Payne et al. (1993). Therefore, experts and novices may adopt different strategies across different levels of task complexity. While prior studies have examined the effects of users’ expertise and task complexity separately, the interaction of these factors is not well understood. Thus, we have developed the following hypothesis:

$H1$: The interaction between user expertise and task complexity influences the adoption of ask-directed search and browsing strategies.

3.2.2  The moderating role of the knowledge management support

During knowledge seeking, knowledge-seeking strategies might vary according to the seeker’s perception of knowledge management support. Knowledge seekers often evaluate the results of their knowledge-seeking outcomes and then decide whether to stop or change the search (Marchionini, 1995).

In our study, we proposed that when perceived KMS quality or knowledge content quality is poor, the interaction of users’ expertise and task complexity is likely to have a weaker impact on the adoption of knowledge-seeking strategies. Conversely, when the KMS or knowledge content quality is perceived to provide high capability, seekers facing high or low task complexity will adopt more knowledge-seeking strategies. These arguments lead to the following hypotheses:

$H2a$: When the level of the user’s perceived knowledge content quality is high, the interaction between user expertise and task complexity influences the adoption of ask-directed search and browsing strategies.

$H2b$: When the level of the user’s perceived KMS quality is high, the interaction between user expertise and task complexity influences the adoption of ask-directed search and browsing strategies.
3.2.3 Influence of knowledge-seeking strategies on task performance

Task completion time, task quality, and user satisfaction are used as indicators of task performance. When seekers are engaged in a focused search behavior, they are typically directed by an intent to make an active search (Gray, 1990). Directed search strategy can focus on specific areas deemed most likely to contain relevant information (Barrick & Spilker, 2003). Thus, directed search is expected to influence users’ task performance.

From the human information-processing view, when seekers adopt a browsing strategy, they save all acquired information in a buffer zone of sensory memory while their sensory memory receives broad stimulation due to external information. After scanning and forgetting partial information, the remaining information is transferred to short-term memory, to be recovered in consciousness through the process of meaningful rehearsal. This affects task understanding and ultimately results in higher task quality. When seekers adopt browsing strategies, they usually have an imprecise goal in mind (Toms, 2000) and tend to scan broadly across a wide variety of knowledge in a KMS. We expect that seekers’ browsing strategies will be positively associated with their task performance. These arguments lead to the following hypotheses:

\[ H3a: \text{Ask-directed search strategy adoption affects task completion time, task quality, and user satisfaction.} \]

\[ H3b: \text{Browsing strategy adoption affects task completion time, task quality, and user satisfaction.} \]

4 RESEARCH METHOD

4.1 Experimental design

A field experiment was conducted to investigate how people would seek knowledge through a professional virtual community. The experimental design was a 2×2 factorial design. The two factors were user expertise (expert versus novice, between subjects) and task complexity (low versus high, between subjects).

4.2 Interviews, pre-test and pilot test

Before the formal experiment, interviews, a pre-test and a pilot test were undertaken.

The interviews were conducted with a total of fifteen first-line managers across ten organizations in Taiwan: department managers, vice-managers, project managers, section managers, etc. These managers met one of the following qualifications: (1) having experiences managing a Java team; (2) having Java work experiences; and (3) having experiences of promoting Java certifications. The purposes of the interviews were to find out (1) the Java certificates; (2) the values of these certificates and the degrees of difficulties in obtaining them; and (3) how to distinguish Java experts from novices. Afterwards, we distinguished among eight Java certifications and defined a standard to separate experts from novices.

A pre-test was examined by five information management experts with experience in the field of knowledge management. They were asked to delete unnecessary or inappropriate questions while modifying ambiguous or inappropriate translated questions. In addition, we sought comments from these experts to reduce ambiguity in the experimental task and experimental procedure.

A pilot test was conducted, prior to the formal experiments, to test (1) the feasibility of the experimental Website, (2) the feasibility of the experimental tasks, (3) the design of the experimental
procedures, (4) the completeness of the experiment description, (5) the suitability of the experimental period, and (6) the design of the experiment questionnaires.

4.3 Experimental subjects

Experimental subjects were selected from members of JavaWorld (http://www.javaworld.com.tw). JavaWorld is a professional Java site in Taiwan. The site has more than 130,000 registered users and has provided over 270,000 articles. The JavaWorld forum offers services such as knowledge sharing, knowledge seeking, technical discussion, job hunting and file uploading. A message with a hyperlink connecting to our experimental website was posted on the JavaWorld homepage. In the first stage, there were 152 subjects responding their background information, with 126 of them having completed the experiment. After the experiment, 7 subjects were dropped from the sample for the following reasons: 3 of them are lack of JavaWorld usage experiences and another 4 subjects were outliers in the task quality and task completion time. Hence, we used a sample of 119 subjects among the four cells of the design (see Figure 2).

<table>
<thead>
<tr>
<th>User Expertise</th>
<th>Expert</th>
<th>Novice</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Task complexity</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Low</td>
<td>n=30</td>
<td>n=29</td>
<td>n=59</td>
</tr>
<tr>
<td>High</td>
<td>n=28</td>
<td>n=32</td>
<td>n=60</td>
</tr>
<tr>
<td>Total</td>
<td>n=58</td>
<td>n=61</td>
<td>n=119</td>
</tr>
</tbody>
</table>

Figure 2. Overview of the experimental design

After the experiment, NT$300 were awarded to each participant for participating and additional cash bonuses (NT$2000, NT$1500 and NT$1000) were awarded to those whose task quality were among the top three. Among the 119 subjects, 23 were females and 96 were males. Most of them (78.2%) had more than one year of JavaWorld experiences. Most of them (84%) had experiences of working with Java. More than half of them had a Java certification (62.2%). Of the 119 participants, 41 were students (34.4%), 7 were university teachers (5.9%) and 71 were employees of a company (59.7%).

4.4 Experimental tasks and website

The low-complexity task was to compute three students’ semester grade; the task involved writing five methods in two classes. The high-complexity task was a movie rental application; the task involved writing seven methods in five classes. Since the experiment results were likely to be influenced by the degree of familiarity with certain tasks and systems, our subjects were requested first to accomplish a practice task.

The experimental website, written in ASP.NET, was developed specifically for this study. Following the instructions on the website, each subject had to accomplish the following tasks: (1) complete the subject’s background information, (2) log into the experimental website, (3) read the description of the experimental procedure, (4) watch a JavaWorld website film about how to seek knowledge in the website, (5) perform the practice task and link to KMS (JavaWorld Forum) to seek knowledge, (6) perform the experimental task and link to KMS (JavaWorld Forum) to seek knowledge. The experimental task had to be completed within 120 minutes and could be extended to 180 minutes at most (based on previous studies and pilot results), and (7) complete the post-experiment questionnaire.

4.5 Experimental procedure

The experimental procedure has two stages. The first stage is the pre-experimental stage. Participants complete a background questionnaire with ten items that include a wide range of demographic, individual differences (including JAVA work experience, certification etc.) and member history. The second stage is the experimental stage. The researcher invited the subjects who had completed the pre-experiment stage to visit the experiment website via email or MSN messenger. Subjects were
entered into the experimental website and provided a brief introduction; the subjects read the
description of experimental procedure and watched a JavaWorld-website film about how to seek
knowledge on the website. After subjects accomplished a practice task, subjects were conducted to
their experimental tasks (low-complexity task or high-complexity task, as assigned by the researcher),
and the system recorded the task start and end times. After completing the experimental task, subjects
answer post-experiment questionnaires.

4.6 Variables

The two independent variables were user expertise and task complexity. User expertise represents the
degree to which an individual has the necessary skills and abilities to perform at the highest level
(Shanteau, 1992). Users were classified as experts or novices. As suggested by Shanteau (1992),
expertise is reflected by official recognition or job titles. The background information of the subjects
collected in the first stage was comprised the following: (1) whether the subject had a Java-related
certification and (2) whether the subject was a full-time or a part-time programmer with work
experience on Java projects. Task complexity represents the degree of effort required to complete a
task (Benbasat & Lim, 1993). Task complexity was identified as either high or low. The low-
complexity task was to compute three students’ semester grade. The high-complexity task was to
complete a movie rental application. The two tasks had been previously tested and validated
(Balijepally et al., 2009).

The two moderating variables were perceived knowledge content quality, and perceived KMS quality. Perceived knowledge content quality represents a user’s perception of the quality of the knowledge content that the KMS produces (DeLone & McLean, 1992). Perceived KMS quality represents a user’s perception of the performance of the KMS itself (DeLone & McLean, 1992). After finishing each task, the subjects were asked to rate the knowledge content quality with four items and the KMS quality with five items. Each item used a seven-point Likert scale (1=strongly disagree and 7=strongly agree).

The two process variables were ask-directed search strategies and browsing strategies. Ask-directed search strategy represents the approach that people use when they have specific information needs in mind and actively search for on-topic information (Zhang & Watts, 2008). Browsing strategy represents the approach that people use when they are briefly scanning large quantities of information for possible relevance to their information needs (Zhang & Watts, 2008). The measurement of ask-directed search strategies was adapted from Vandenbosch and Higgins (1996) and was developed based on the study of Hertzum and Frøkjær (1996) for the KMS search tools. Keyword-based searching is currently considered a more fruitful knowledge-seeking strategy (Chen et al., 1998). The measurement of browsing strategies was adapted from Vandenbosch and Higgins (1996). All measurement items were discussed during the pre-test stage. Based on the feedback, some questions were rephrased while some were dropped. A pilot study provided further feedback on the appropriateness of the questions. Four items for searching strategies and four items for browsing strategies were then consolidated into a final survey. Each item used a seven-point Likert scale.

The three dependent variables were task completion time, task quality, and user satisfaction. To measure task completion time, the experimental website automatically recorded the time (in minutes) when the subjects start and finish the task. Task quality represents the assessment result of the quality of the programming task performed by the subjects (Balijepally et al., 2009). To rate the task quality of the two tasks, two separate assessment rubrics were adopted from Balijepally et al. (2009) and were slightly modified for the score scale of 0–100. Three people (two project managers and one university teacher), not directly related to the study, were trained as judges. The assessment rubrics were further modified based on the judges’ experiences in scoring programming tasks. Each subject was independently assessed by the three judges according to the assessment rubrics. The average of the scores given by the three judges was used as the task quality score. User satisfaction represents the subjective evaluation of the overall outcomes due to knowledge seeking from the KMS (Kulkarni et al., 2006). User satisfaction was measured according to the Seddon and Yip (1992) overall satisfaction measure with four items. Each item used a seven-point Likert scale.
Two control variables were identified, which could influence the participants’ knowledge-seeking strategies: frequency of prior KMS usage and KMS self-efficacy. Participants were asked to respond to one question about the frequency of their KMS usage (from 1=many times per day, 2=many times per week, 3=many times per month, 4=once in six months, and 5=once over six months). Participants were asked to respond to three items about KMS self-efficacy that were adapted from Taylor and Todd (1995). Each item used a seven-point Likert scale.

4.7 Manipulation check

For the analysis of the manipulation check regarding user expertise, the results confirmed that the “expert” group had more certification than the “novice” group (M=1.88 for the “expert” group, and M=0.30 for the “novice” group, t=-13.104, p=0.000). For the analysis of the manipulation check regarding task complexity, the researcher obtained independent evaluation results of the tasks by three experts (two project managers and one university teacher, who were also the expert judges of task quality), confirming that the movie rental application was more complex than the student scoring task. The experts responded to two questions “How do you feel about the movie rental task you performed, as compared to the student scoring task?” using Likert scales from (1) very easy to (7) very difficult and (1) very simple to (7) very complex. The mean score was 6.33, providing further evidence of the success of the task complexity manipulations.

5 RESULTS

5.1 Reliability and validity

The constructs were assessed for reliability using Cronbach’s alpha and composite reliability. Nunnally (1978) suggested that the acceptable value for Cronbach’s alpha was above 0.7. The coefficients used for all constructs ranged from 0.74 to 0.88, in which all measures surpassed the 0.7 criteria. The composite reliability had also led to very similar results ranged from 0.75 to 0.90, all measures higher than the recommended level of 0.7 (Nunnally, 1978). In order to assess construct validity, principal component analysis with varimax rotation was performed. Factor analysis yielded six components with eigenvalues above 1. The factor loading of browsing strategy (BS1) was below 0.5 and thus was omitted. Other questions had at least good loadings on the intended constructs. Convergent validity is demonstrated when item loading exceeds the acceptable value of 0.5 recommended by Hair et al. (2006) on their corresponding constructs, and AVE (average variances extracted) of the construct is larger than 0.5, exceeding the threshold value suggested by Fornell and Larcker (1981). All of the factors exceeded the threshold value of 0.5 and the AVE for all constructs exceeded the threshold value of 0.5. Discriminant validity is demonstrated when the square root of the AVE from the construct is greater than the inter-construct correlations, as suggested by Fornell and Larcker (1981).

5.2 Hypotheses testing

The MANCOVA results (Table 2) show that the interaction of user expertise and task complexity had a significant influence on the adoption of ask-directed search strategies (p=0.002) and browsing strategies (p=0.001). Thus, hypothesis H1 was supported.

<table>
<thead>
<tr>
<th>Dependent variable : Ask-directed search strategy</th>
<th>Source</th>
<th>SS</th>
<th>MS</th>
<th>F</th>
<th>Sig.</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>KMS self-efficacy (Covariate)</td>
<td>0.236</td>
<td>0.236</td>
<td>0.188</td>
<td>0.665</td>
</tr>
<tr>
<td></td>
<td>Frequency of prior KMS usage</td>
<td>5.015</td>
<td>5.015</td>
<td>4.006</td>
<td>0.048*</td>
</tr>
</tbody>
</table>

* Significant at the 0.05 level.
Table 2. MANCOVA results (H1)

When the level of a user’s perceived knowledge content quality is high, the MANCOVA results (Table 3) show that the interaction of user expertise and task complexity has significant effects on the adoption of ask-directed search strategies ($p=0.013$) and the adoption of browsing strategies ($p=0.049$). Thus, hypothesis H2a was supported.

Table 3. MANCOVA results (H2a: Perceived knowledge content quality is high)

When the level of a user’s perceived KMS quality is high, the MANCOVA results (Table 4) show that the interaction of user expertise and task complexity has significant effects on the adoption of ask-directed search strategies ($p=0.001$) and the adoption of browsing strategies ($p=0.032$). Thus, hypothesis H2b was supported.
Regression analysis was adopted to test the effects of ask-directed search and browsing strategies on task completion time, task quality, and user satisfaction. The ask-directed search strategy affects the task completion time ($\beta = -0.348$, $p < 0.01$), task quality ($\beta = 0.312$, $p < 0.01$) and user satisfaction ($\beta = 0.163$, $p < 0.1$). Thus, hypothesis H3a was supported. On the other hand, the browsing strategy has no effect on task completion time ($\beta = -0.118$, NS) and task quality ($\beta = -0.086$, NS). However, it affects user satisfaction ($\beta = 0.232$, $p < 0.01$). Thus, hypothesis H3b was partially supported.

The results of hypotheses testing are summarized in Table 5.

<table>
<thead>
<tr>
<th>Hypotheses</th>
<th>Supported?</th>
</tr>
</thead>
<tbody>
<tr>
<td>H1: The interaction between user expertise and task complexity influences the adoption of ask-directed search and browsing strategies.</td>
<td>Yes</td>
</tr>
<tr>
<td>H2a: When the level of the user’s perceived knowledge content quality is high, the interaction between user expertise and task complexity influences the adoption of ask-directed search and browsing strategies.</td>
<td>Yes</td>
</tr>
<tr>
<td>H2b: When the level of the user’s perceived KMS quality is high, the interaction between user expertise and task complexity influences the adoption of ask-directed search and browsing strategies.</td>
<td>Yes</td>
</tr>
<tr>
<td>H3a: Ask-directed search strategy adoption affects task completion time, task quality, and user satisfaction.</td>
<td>Yes</td>
</tr>
<tr>
<td>H3b: Browsing strategy adoption affects task completion time, task quality, and user satisfaction.</td>
<td>Partially supported</td>
</tr>
</tbody>
</table>

Table 5. Results of hypotheses testing

6 DISCUSSION

6.1 Discussion of the results

This study addressed the possibility of differences in ask-directed search and browsing strategies between experts and novices across different levels of task complexity. Experts adopt more ask-directed search strategies than novices across different levels of task complexity. In particular, when facing high-complexity tasks, experts adopt more ask-directed search strategies than novices. On the other hand, when facing low-complexity tasks, experts adopt more browsing strategies than novices, but for high-complexity tasks, novices adopt more browsing strategies than experts (see Figure 3).

We further compare the effects of low and high perceived knowledge content quality on the interaction of user expertise and task complexity. Table 6 provides a comparison among users, tasks, and users’ perception of knowledge management support on the adoption of knowledge-seeking strategies.

This study also addressed a possible association between the adoption of knowledge-seeking strategies (ask-directed search and browsing strategies) and task performance. The findings are
summarized below. First, when ask-directed search strategies are adopted, less time is required to complete the task, task quality is improved, and perceived user satisfaction is higher. We suggest that the adoption of an ask-directed search strategy fosters a greater exploration of data, leading to higher task quality, improved task efficiency, and higher user satisfaction. With an ask-directed search strategy, a user can quickly obtain feasible solutions by querying “what is” scenarios. Second, it is interesting to note that participants who adopt browsing strategies indicate higher levels of satisfaction, irrespective of their task performance, in terms of task completion time and task quality.

### Table 1: Marginal Means of Ask-directed Search and Browsing Strategies

<table>
<thead>
<tr>
<th></th>
<th>When a user’s perceived knowledge content quality is low</th>
<th>When a user’s perceived knowledge content quality is high</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>AS</strong></td>
<td>The interaction between user expertise and task complexity has no influence on the adoption of ask-directed search strategies. Experts always adopt more ask-directed search strategies than novices across both levels of task complexity.</td>
<td>The interaction between user expertise and task complexity has influence on the adoption of ask-directed search strategies. Experts adopt more ask-directed search strategies than novices. With high-complexity tasks and high perceived knowledge content quality, experts adopt more ask-directed search strategies than novices.</td>
</tr>
<tr>
<td><strong>BS</strong></td>
<td>The interaction between user expertise and task complexity has influence on the adoption of browsing strategies. With low-complexity tasks and low perceived knowledge content quality, experts adopt more browsing strategies than novices, whereas with high-complexity tasks and low perceived knowledge content quality, novices adopt more browsing strategies than experts.</td>
<td>The interaction between user expertise and task complexity has influence on the adoption of browsing strategies. With low-complexity tasks and high perceived knowledge content quality, experts adopt more browsing strategies than novices, whereas with high-complexity tasks and high perceived knowledge content quality, novices adopt more browsing strategies than experts.</td>
</tr>
</tbody>
</table>

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The MANCOVA results show that the interaction of user expertise and task complexity has no significant effect on the adoption of ask-directed search strategies ($p=0.142$) but has significant influence on the adoption of browsing strategies ($p=0.003$).
When a user’s perceived KMS quality is low:

**AS**: The interaction between user expertise and task complexity has no influence on the adoption of ask-directed search strategies. Experts always adopt more ask-directed search strategies than novices across both levels of task complexity.

<table>
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<tr>
<th>When a user’s perceived KMS quality is high</th>
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<tr>
<td><strong>AS</strong></td>
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<td><strong>BS</strong></td>
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</table>

AS: ask-directed search strategy; BS: browsing strategy

Table 6. Summary of results on the moderating effect of perceived knowledge content quality and KMS quality

### 6.2 Implications for research and practice

This study contributes to the KMS and the cognitive psychology literature in several important aspects.

First, regarding the cognitive psychology literature, studies on expertise in many domains have indicated that experts and novices have different information-seeking strategies (Tabatabai & Shore, 2005). Information seeking is determined by concurrent interactions among the user, task, setting, domain, and system factors (Marchionini, 1995). This study has extended this stream of research by investigating the interactions among user expertise, task complexity, and the moderating role of users’ perception of knowledge management support on the adoption of knowledge-seeking strategies.

Second, prior research across many domains, such as accounting, engineering, and programming, has indicated that user expertise is an important factor in explaining task performance. These studies point out that user expertise has a positive effect on task performance. However, they have failed to examine whether the interaction among user expertise and task complexity affects performance indirectly through some other variables (e.g., seeking strategy). The results indicated that the interaction of different levels of user expertise and different levels of task complexity affects the adoption of ask-directed search strategies and browsing strategies. The results will be useful to current KMS research.

Finally, less task completion time and higher task quality are associated with users’ adoption of ask-directed search strategies, whereas higher user satisfaction is associated with users’ adoption of ask-directed search or browsing strategies. This study contributes to the KMS literature by providing empirical support for the joint effects of the adoption of knowledge-seeking strategies and task performance.

This study also contributes to both the KMS developer and the managers.

First, the results indicate that with high-complexity tasks and high perceived KMS quality, experts adopt more ask-directed search strategies than novices. High-complexity tasks require more cognitive

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2 The MANCOVA results show that the interaction of user expertise and task complexity has no significant influence on the adoption of ask-directed search strategies ($p=0.578$) but has significant influence on the adoption of browsing strategies ($p=0.001$).
effort, and the actual amount of information needed to solve the problems is greater as well (Balijepally et al., 2009). Thus, KMSs must be designed with easy-to-use search tools such that novices can readily find knowledge without feeling overwhelmed.

Second, the results reveal that successful seekers reflect on the ask-directed search strategies that they adopt. Thus, managers should provide novices with functional training while reinforcing search skills. In addition, KMS developers can use several techniques to improve indexing and facilitate searching, such as natural language queries, taxonomy, and semantic network-based indexing.

Finally, the results indicate that experts adopt more ask-directed search strategies than novices across different levels of task complexity. In particular, with high-complexity tasks, experts adopt more ask-directed search strategies than novices. However, with high-complexity tasks, novices adopt more browsing strategies than experts. We suggest to managers promoting KMS that appropriate training courses should be arranged and conducted according to employees’ individual differences.

7 CONCLUSION

This study aims at studying how user expertise, task complexity, and users’ perception of knowledge management support influence the adoption of knowledge-seeking strategies and user task performance. This study provides theoretical and practical contributions in three ways. First, it systematically and simultaneously explored how user expertise, task complexity, and perception of knowledge management support affect the adoption of knowledge-seeking strategies. Second, a field experiment was performed to show causation. Third, it measured the relationship between adopted seeking strategies and task performance.

References


