Decision Support Systems 53 (2012) 482–489

Contents lists available at SciVerse ScienceDirect

Decision Support Systems

journal homepage: www.elsevier.com/locate/dss

The knowledge demands of expertise seekers in two different contexts: Knowledge allocation versus knowledge retrieval

Dorit Nevo [a,*], Izak Benbasat [b], Yair Wand [b]

[a] Schulich School of Business, York University, Canada
[b] Sauder School of Business, University of British Columbia, Canada

ARTICLE INFO

Article history:
Received 2 February 2011
Received in revised form 22 December 2011
Accepted 19 March 2012
Available online 29 March 2012

Keywords:
Expertise location
Knowledge allocation
Knowledge retrieval
Information systems
Expert selection decision

ABSTRACT

This paper explores the knowledge demands of expertise seekers for the purpose of designing effective expertise locator systems. We conduct an empirical investigation, using conjoint analysis and within-subject tests, to determine the relative importance assigned to different expert attributes under two expertise seeking contexts: knowledge allocation and knowledge retrieval. Our results show that when choosing an expert to retrieve knowledge from (knowledge retrieval), expertise seekers will assign greater importance to the person's level of expertise. When selecting an expert to transfer knowledge to (knowledge allocation), attributes representing the network ties between the expert and the seeker as well as the benevolence of the expert will be perceived as more important. These results are important for the design of expertise locator systems that are better customized to fit the knowledge needs of their users, and to serve the organization as a whole.

1. Introduction

Organization members possess unique expertise that benefits the organization by enabling improved work processes, decision-making, knowledge synergies, and innovation. Indeed, organizational innovation often entails the combination of people and knowledge, creating new connections between people and their ideas and resources such that new combinations emerge [33]. Locating where this expertise resides and coordinating its utilization are therefore of great importance to organizations.

However, these activities are also quite challenging. For example, a survey of professionals in medium and large companies (with 1000 or more employees) revealed that when it comes to locating expertise, about one third did not know of people in the company who may potentially help them to do their job better; moreover, 61% could not locate these people [10]. Studies on strategies applied in locating expertise have shown that people tend to look in their vicinity, examine historical documents, or, as organizations grow and become more dispersed, turn to connectors (sometimes referred to as “expertise concierges”) to identify potential experts [2,27]. Consequently, *expertise locator systems* – information systems designed to support the identification and location of organizational expertise – are increasingly being utilized in organizations, albeit with numerous challenges and limited success [2,17,27,45].

Indeed, locating expertise in organizations is not an easy task. Searching for experts beyond one's immediate group of colleagues requires, first and foremost, having knowledge of who knows what in the organization and being able to track expertise as employees develop skills, join and leave the organization, and take on new tasks and responsibilities [30,32]. However, location and identification of expertise is only part of the challenge. Even if organizations are successful at providing accurate and comprehensive expertise directories to their employees, the *selection of experts* is another challenging decision for organization members [27]. Distinct from the location and identification of relevant expertise, expert selection refers to choosing from among the identified possibilities the most appropriate experts to consult with. Such decision requires an evaluation of the experts based on knowledge that is often not available to the decision maker.

This paper focuses on the expert selection problem, which is of particular relevance in an environment where communication is mediated by technology, where employees are not collocated, may be unfamiliar with each other, or have limited knowledge of each other's expertise. IT-based expertise locator systems can help employees locate and select experts. Expertise locator systems are tools aimed at supporting the location of expertise within the organization, ranging from online white pages backed by user profiles to more sophisticated Web and email mining systems, automated profiling systems, and use of various intelligent agents and social computing tools [2]. Industry examples include Oracle's Beehive collaboration software, specific modules within Microsoft's SharePoint, and IBM's BluePages.

A key objective of expertise locator systems is to provide users with information that effectively enables not only locating expertise but also deciding and selecting among relevant experts [30]. To facilitate the design of such systems it is necessary to identify which information can be useful in deciding among experts whom the

* Corresponding author.
E-mail addresses: dnevo@schulich.yorku.ca (D. Nevo), izak.benbasat@ubc.ca (I. Benbasat), yair.wand@ubc.ca (Y. Wand).

0167-9236/$ – see front matter © 2012 Elsevier B.V. All rights reserved.
doi:10.1016/j.dss.2012.03.005

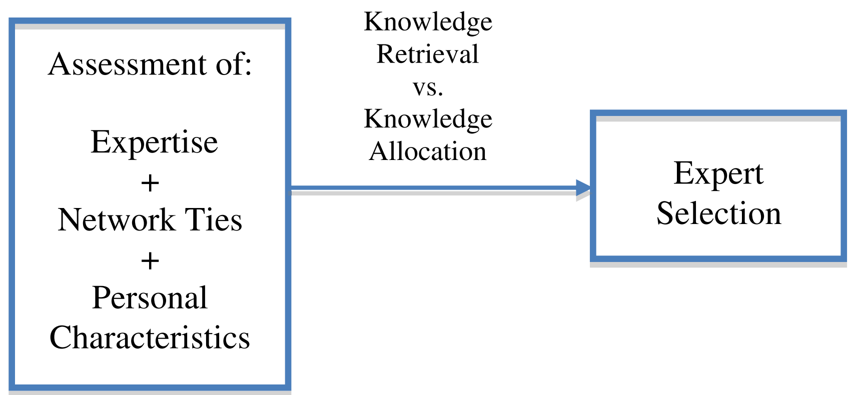

Fig. 1. Knowledge demands for expert selection.

knowledge seeker is not personally familiar with. Consequently, in this study we examine the attributes of the experts that expertise seekers may use in making their selection decision.

For the conceptual foundation of this study, we rely on several bodies of literature. First, transactive memory theory is a theory of expertise location and coordination [22,43]. As groups are formed, their members evaluate each other's knowledge and expertise and encode this information in directories of meta-memory, indicating who knows what within the group. When new knowledge enters the group, it is allocated to the group's expert on the topic. Similarly when knowledge is required beyond one's own area of expertise, the group's expert on the topic is approached to obtain this knowledge [43]. Transactive memory theory provides two important foundations for this study. First, the use of meta-memory to locate and coordinate expertise within the group can be utilized in technology-mediated environments [7,18,32,34]. Second, transactive memory theory defines two important contexts which we study in this paper: *knowledge retrieval* – searching an answer from an expert; and *knowledge allocation* – selecting an expert to transfer new knowledge to. However, because the expertise selection problem discussed in this paper may also apply to cases where people seek expertise outside their group, from unfamiliar sources, and on an ad hoc basis we employ a broader foundation to study the expertise selection decision, as explained in the next section.

The objective of the study presented in this paper is thus to provide a better understanding of the relative importance of expert attributes given knowledge retrieval *versus* knowledge allocation *objectives.* Although this investigation focuses on human-to-human information sharing, technology can play an important role in enabling the sharing of expertise by supporting the location of expertise and decision of what experts to approach, and by mediating the sharing process. Indeed, without technology, such sharing of information would be greatly limited, as employees may be unaware of expertise which exists elsewhere in the organization and therefore will have limited access to this expertise. In this context, we believe that this study can offer an important contribution in understanding the information required by knowledge workers in order to decide where to look for knowledge or whom to allocate knowledge. This understanding in turn can help better determine the requirements of expertise locator systems and guide the design of interfaces for such systems.

2. Foundation

We reviewed the literature on expertise selection [e.g. 4,9,27,29–31,37,45], knowledge transfer [19–21,40], transactive memory [5,7,15,16,18,22,23,28,32,34,35,43], and information quality [39,42] from the perspective of making a decision about experts' selection. Synthesizing this literature we found that three types of knowledge are used to make decisions about the selection of experts, as illustrated in Fig. 1. First is the knowledge about the person's expertise, its value and cost [4]. Second, knowledge of any pre-existing relationship between the expert and the expertise seeker is also of relevance. For example, depending on the expertise sought, an evaluation of strong versus weak network ties may take place, where strong network ties indicate those individuals close to the expertise seekers and are generally thought to facilitate the transfer of tacit knowledge. Weak ties indicate those individuals not directly linked to the expertise seeker, and as such enable access to a wider and richer knowledge base, offering value in terms of acquiring new knowledge [21]. Third is knowledge of particular attributes of the expert, such as the expert's willingness to help, ability to communicate their knowledge, or other personal characteristics [e.g. 9,39].

Studying these three types of knowledge within a decision context, there may be differences in the relative importance of specific expert attributes for making a knowledge retrieval decision versus a knowledge allocation decision. Transactive memory theory defines *knowledge retrieval* as the process in which a member of the group identifies a need for knowledge. That person will then evaluate his or her own "feeling of knowing" before searching for the group's expert on the topic [43]. The literature reviewed identifies a person's expertise as most important for retrieving knowledge from that person. An expert's knowledge of others' expertise, frequent and effective communications between an expert and the knowledge seeker, and knowing and valuing the knowledge possessed by the expert are important factors in the knowledge retrieval decision [4,15,23]. *Hence we expect that attributes contributing to the perceptions of a person's expertise will be perceived as most important for knowledge retrieval.*

Knowledge allocation refers to a situation in which a member of the organization obtains knowledge that may be relevant to others and needs to locate the best person (or persons) to convey/transmit this knowledge to [43]. Consider, as an example, a sales person who obtains some strategic information concerning a competitor (for example the development of a new product or targeting a new market) and wishes to forward that knowledge to the most suitable person within the organization. The sales person may need to select among several individuals within the organization, and may require specific knowledge to make this allocation decision.[1] In expertise literature, knowledge allocation has been rarely studied in and of

[1] We acknowledge that some members of the organization by their role definition may be viewed as possessing expertise or as requiring specific knowledge. Nevo and Wand [32] referred to this distinction as required role knowledge versus non-required instance knowledge. Indeed there may be situations in which one is required to allocate knowledge on a need basis (for example to a department manager). However, in this paper our focus is on situations in which one faces a choice among a subgroup of potential experts and a selection decision is warranted, regardless of how this subgroup is identified (be it role knowledge, instance knowledge, or both). In other words, we do not deal with the situation in which only a single person possesses the required expertise.

itself. Examining related literature on knowledge transfer and on contributions to online communities of practice indicates that *reciprocity expectations* and norms play a key role in knowledge contributions and transfer [20,40].

Rooted in social exchange theory [3], expected reciprocity in the context of knowledge transfer has been defined as a probabilistic calculation that the benefits from the exchange will outweigh the risk that it will not be reciprocated [19]. From this point of view, in the context of knowledge allocation, one is expected to select an expert to allocate knowledge to base on knowing that he or she would be able to retrieve the knowledge as needed, or that this knowledge could be used to benefit the organization. *Hence we expect that attributes contributing to reciprocity expectations will be perceived as most important for knowledge allocation.*

2.1. Hypotheses

The objective of this study is to understand the use of expert attributes in the selection decision under two contexts — knowledge retrieval versus knowledge allocation. For the reasons explained above, we expect differences in the perceived importance of attributes in each of the two contexts. To develop our hypotheses, we begin by identifying a set of expert attributes used in the selection decision. According to the transactive memory theory, information on the subject and location of knowledge within the group (i.e. who knows what) is needed [35,43]. In addition, as discussed above, other knowledge may be needed to identify the suitable expert for a given task, for example perceptions of each other's reliability, competence, and trust [1,23,35]. Encoding such information is all the more important in the technology-mediated environment to compensate for the lack of face-to-face communications and familiarity [32].

The most prominent attributes identified in the transactive memory and related literature concern perceptions of the credibility, trustworthiness, and the level of expertise and depth of knowledge of team members (e.g. [1,5,23,31,35]). We rely on related literature to operationalize these attributes for the technology environment. Specifically, Wathen and Burklell [41] link credibility with trustworthiness and expertise. Mayer et al. [25] in turn associate trustworthiness with a person's ability (or competence), benevolence, and integrity. Whitener et al. [44] further note that a person's perception of the trustworthiness of others is affected by attributes of the communications between them, including the frequency of the communication, the adequacy of the explanations provided, and the openness of the communication. Finally, assessing trustworthiness can also be supported by information on the social network of the expert. For example, information on the network ties that lie between the expert and the expertise seeker may lead to trust through common ties [6,21]. With respect to expertise, we note that beyond identifying a person's expertise in a specific domain, Cross and Sproull [8] also identified referrals as an important type of actionable knowledge and part of a person's expertise.

Building on the above, in our study of knowledge allocation versus retrieval, we study the relative importance of the following five attributes[2]:

(1) *Willingness to help*: representing the potential expert's willingness to help the expertise seeker.
(2) *Communications skills*: representing the ability of the potential expert to clearly communicate their knowledge to the expertise seeker.
(3) *Network ties to the respondent*: representing the network distance (i.e. degrees of separation) between the expertise seeker and the potential expert.
(4) *Self-identified expertise level*: representing the extent that the potential expert feels he or she has expertise in the domain of the knowledge.
(5) *Knowledge of others' expertise*: representing the ability of the potential expert to point in the direction of other experts in the domain.

Referring back to Fig. **1**, the above attributes span knowledge on a person's expertise, network ties to the respondent, and personal characteristics.

As discussed earlier in this paper we expect attributes representing expertise to be perceived as more important for knowledge retrieval than knowledge allocation. Accordingly we hypothesize that:

H1. A potential expert's self-rated expertise and knowledge of others' expertise will be perceived as more important for knowledge retrieval than for knowledge allocation.

We expect attributes related to reciprocity expectations to be perceived as more important for knowledge allocation. Kachra and White [19] observed that expected reciprocity is related to strong social relationships and perceived competition. Hence, we expect knowledge of a potential expert's social ties to the expertise seeker and of that potential expert's benevolence or willingness to help to be more important in the allocation context. Accordingly,

H2. A potential expert's willingness to help and their network ties to the expertise seeker will be perceived as more important for knowledge allocation than for knowledge retrieval.

Finally we note that the potential expert's communication skills can be linked both to allocation and retrieval as it has been identified as a component of a person's expertise as well as a contributor for a person's trustworthiness [44]. Therefore we *do not expect to find a significant difference in the importance assigned to a potential expert's communications skills.*

In the next section, we discuss the methodology used to test these hypotheses.

3. Methodology

The above hypotheses focus on the trade-offs we expect respondents (i.e., expertise seekers) to make in terms of experts' attributes when engaging in knowledge allocation versus knowledge retrieval decisions. A suitable methodology to explore such trade-offs is conjoint analysis. *Conjoint analysis* is a multivariate technique originating in mathematical psychology [13]. It is a decompositional approach in understanding choices and decisions, relying on a basic assumption that a person's preferences toward an alternative (such as a product or a service or, in this study, a specific expert) can be decomposed to derive the values the individual places on the attributes of that alternative [11,14].

In conjoint analysis, an alternative is introduced in terms of a bundle of its characteristics, or *attributes*. For example, instead of evaluating various laptop computers, respondents are asked to evaluate various combinations (bundles) of attributes of laptops, such as processor type, screen size, weight, and price. Such combinations are termed *profiles*. Each profile contains a description of the attributes of a different alternative and the specific values, or *levels*, assigned to each attribute (in the laptop example, one profile example can be: processor: Intel Core i3, screen size: 14″, weight: 5lbs, price: $450). The goal of conjoint analysis is to identify the relative importance (and thus the trade-offs) placed by respondents on the specific attributes during the decision-making process.

[2] Note that, while our hypotheses focus on five specific attributes, our findings could be generalized to other attributes representing expertise and reciprocity. We discuss the generalizability of our findings later in the last section of the paper.

Conjoint analysis provides two main measures: part-worth utility estimates and importance weights of the attribute. The part-worth utility estimates indicate the relation between each of the attributes' levels and the preferences of the individual. Positive values mean that the attribute's level is positively related to preference. The importance values represent the relative importance of each attribute in the overall preference order of the individual.

Conjoint analysis can be used to study the trade-offs people are willing to make between attributes of each alternative, to identify the overall benefits of different alternatives, to estimate the relative importance of attributes of alternatives, and to estimate whether a particular attribute has significance in making a choice [36]. It was chosen as the method for this study because it closely mimics our phenomenon of interest — the expert selection decision. When selecting experts, individuals choose a person rather than specific attributes of a person. Similarly, the real life decision which we study entails the evaluation of bundles as opposed to the evaluation of individual attributes. Nevertheless, such attributes play an important role in driving the selection of experts and hence a decompositional approach which deduces the value of individual attributes from the evaluation of the bundle as a whole is called for. Using conjoint analysis in the context of this study can allow us to understand the trade-offs that people make between different attributes of the expert and the importance of specific attributes in the decision process.

There are several other benefits for using conjoint analysis in a decision-making context over compositional, self-explicating methods (such as traditional surveys) that ask people to state the desirability and importance of specific attributes. First, in conjoint analysis, decision makers are faced with options that vary across two or more attributes and therefore are forced to make trade-offs that more closely imitate real life decisions. Second, in the self-explicating process, when responding to questions such as 'how important is attribute A to you?', respondents might provide the socially desirable answer rather than their true valuation of the attribute (for example, a person may state that job satisfaction is more important than salary, but in reality might choose the job with the higher salary over the more satisfying one). Third, if some attributes are correlated, for example gas mileage and economy of a car, double counting is more likely to occur in the self-explicating method than in conjoint analysis. Finally, conjoint analysis allows greater flexibility in defining the model and does not limit the researcher to define a linear relationship between specific levels of attributes (e.g. three different price levels) and a person's preference order, as is the case for most self-explicating models. Thus conjoint analysis enables fitting the best model for the relative desirability of levels of each of the attributes [12,26].

The following subsections discuss first the study's design (questionnaires used, expert profiles provided, and procedures conducted) and then the sample of respondents.

3.1. Design of study

In accordance with our study's objective and hypotheses, the conjoint analysis consisted of two parts, using two separate yet identically designed web-based questionnaires (provided in the Appendix). One questionnaire focused on eliciting the relative importance of attributes in the context of knowledge allocation, and the other focused on eliciting the relative importance of attributes in the context of knowledge retrieval. Each questionnaire used an appropriate scenario as shown below. The scenarios were presented to respondents in random order.

Allocation: You have recently joined the sales team of SuperTech, a company specializing in developing and marketing customer relationship management (CRM) systems. You are visiting one of the company's largest clients, a chemical manufacturer. During a conversation, the client's VP of Sales tells you about the difficulties he is having in producing accurate sales forecasts and then translating them into production forecasts. He tells you, "This is a serious problem for us as we are always over or under producing because we can't forecast demand. The interesting thing is that there is no software package out there that will help us do that. I'm telling you, we would be the first ones to buy something like that!" You have just identified a potentially lucrative new business line for SuperTech. This is not your area of expertise so you need to find the right person within your team to whom you can pass this information.

Retrieval: You have recently joined the sales team of SuperTech, a company specializing in developing and marketing customer relationship management (CRM) systems. SuperTech has been working extensively to secure a large contract with a major bank. Over the past year, the sales team has been involved in numerous product demonstrations and requirements gathering sessions, and it finally looks like the prospect is almost ready to sign. This would be a major win for the company and all eyes are on this deal. As a new member of this team you meet with the client's CIO, who tells you the following: "I love the product and I think it's going to work for us but I'm very concerned that SuperTech does not have much experience in Financial Services. I want to speak to one of your existing customers who is in our industry and who operates under a similar business model. If you can get me this information, we have a deal." You head back to the office and decide to look for expertise from within the sales team.

After reading each scenario, respondents were asked to evaluate profiles of potential experts and either assess their likelihood of passing the information to them (knowledge allocation) or assess their likelihood of approaching them with respect to obtaining information (knowledge retrieval).

The profile of each potential expert consisted of the five attributes described earlier in this paper. For example, the profile description of a potential expert may have appeared as follows:

- Knowledge of others' expertise: *Yes*
- Communications skills: *Good*
- Self-identified expertise level: *High*
- Willingness to help: *No*
- Network ties to you: *Weak*

The survey introduction included the definition for each attribute, its possible values, and an example profile similar to the one above.

In constructing the questionnaires, we used a fractional factorial design [24,38]. If we define the attributes of interest as the five attributes introduced earlier in this paper, and each attribute is assigned two possible levels (e.g., yes/no, high/low), then a full factorial design implies that all possible combinations of factors and levels are reviewed by respondents, which in our case would be 2^5 or 32 profiles to evaluate. Utilizing a fractional factorial design allows for the evaluation of a smaller number of profiles, in our case the eight listed in Table 1.

The profiles were presented to respondents in a list format (similar to the above example) and for each profile, respondents were asked to indicate their likelihood of selecting the expert described in the profile for the particular purpose of consulting or informing. We used an 11-point scale to evaluate the likelihood of selecting the expert described in the profile to either pass knowledge to (allocation) or consult for knowledge (retrieval). The scale ranged from "not at all likely" on the one end to "will certainly pass the knowledge" (allocation) or "will certainly consult" (retrieval) on the other. The center point represented a neutral view.

In addition to the eight profiles used to estimate the model, two more validation profiles were included in the survey [14]. The validation profiles were similar in form to those described in Table 1 and respondents evaluated them in the same manner they did to the other profiles. The validation profiles, however, were not used in the

Table 1
Conjoint profiles.

Attribute	Levels	Profile 1	Profile 2	Profile 3	Profile 4	Profile 5	Profile 6	Profile 7	Profile 8
Knowledge of others' expertise	Yes/no	No	No	Yes	Yes	Yes	No	No	Yes
Communications skills	Good/poor	Poor	Good	Good	Poor	Poor	Poor	Good	Good
Self-identified expertise level	High/low	Low	High	High	Low	High	High	Low	Low
Willingness to help	Yes/no	No	No	Yes	Yes	No	Yes	Yes	No
Network ties to you	Strong/weak	Strong	Weak	Strong	Weak	Weak	Strong	Weak	Strong

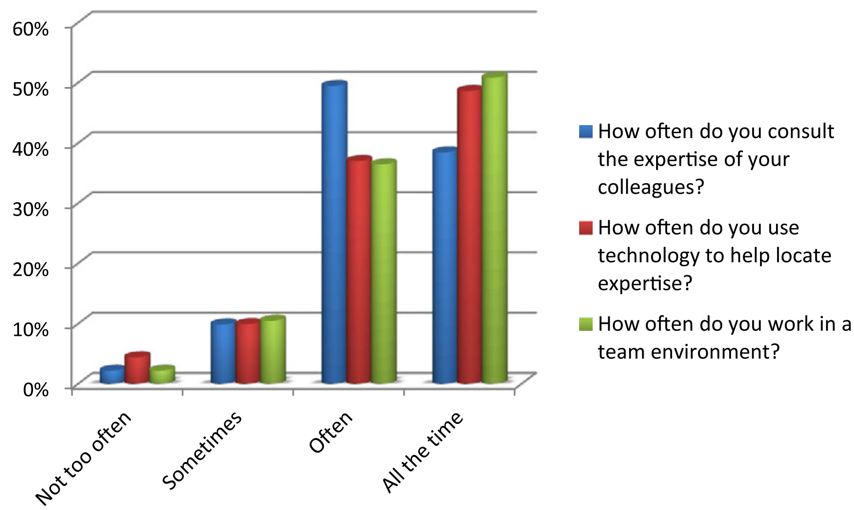

Fig. 2. Characteristics of respondents.

actual fitting of the regression model but instead were used to test the predictive ability of the derived model (comparing predicted and actual values). Finally, one repeated profile was also included for reliability purposes, to ensure responses were consistent for the two identical profiles. Overall respondents evaluated eleven profiles under each task and using an 11-point scale. The least squares regression model was used as the estimation method, as is common in many conjoint studies.

3.2. Respondents

We sent online invitations to a random sample of 1000 English speaking, North-American members of a LinkedIn Web 2.0 community with approximately 12,000 members worldwide. Members of this community are all professionals who share an interest in various aspects of Web2.0. A total of 199 responses were received of which 180 were valid and used in the conjoint analysis, for a final response rate of 18%. Such response rate is not uncommon for Web based surveys. Further, the absolute number of responses (180) is acceptable for conjoint analysis studies [14]. The average respondent, or expertise seeker, had slightly over 15 years of work experience and had been working in his/her current position for about 3.5 years. Of the total number of respondents, 24% were female and 76% were male. Fig. 2 provides additional information on respondents in this study in terms of their expertise seeking habits. As the figure shows, the majority of respondents work in a team environment, actively consult colleagues for knowledge outside of their own expertise, and often use technology to locate expertise.

4. Findings of conjoint study

Testing our hypotheses to study the difference between the relative importance of attributes in the allocation and retrieval processes, we followed two key steps. We first computed, for each respondent, the preference order of attributes under each of the two scenarios, using the conjoint syntax in SPSS. We then followed with within-subject testing of the difference in importance weights for the two scenarios, as described below.

4.1. Conjoint analysis

For each respondent a *regression model* was estimated using eight of the profiles (excluding the validation profiles), with the respondent's rating as the dependent variable and attributes' levels as the independent (dummy) variables. The results of these regressions provided, for each respondent, part-worth utilities for each attribute's level, representing its contribution to the overall utility assigned to the various profiles by the respondent. An importance weight was also calculated for each attribute based on the magnitude of its levels' part-worth utilities; higher magnitude meaning the attribute is more important to the respondent. At the end of this process, a preference order of attributes and their importance (out of 100%) was obtained for each respondent under each of the two scenarios.

As a measure of the quality of the conjoint model, Pearson correlations were computed between the model estimated and actual ratings of each profile. The aggregated Pearson's R value for the allocation scenario was 0.992 (significance of 0.000) and for the retrieval scenario, 0.987 (significance of 0.000). In addition, as an indication of the predictive ability of the model, similar correlations were calculated for the two validation profiles which were not used to estimate the regression model. The aggregated Pearson's R values for the validation profiles were 0.781 (significance of 0.000) for the allocation context and 0.792 (significance of 0.000) for the retrieval context.[3]

On average, all attributes were perceived as important by survey respondents with importance weights (on a percentage scale)

[3] Pearson's R value for the validation profiles are generally expected to be somewhat lower than those computed for the model.

ranging from 14% to 26%. However, because conjoint analysis is conducted at the individual level (i.e. a preference model as estimated for each respondent in the study), it is not advisable to report *aggregated* descriptive statistics of the conjoint results. To further analyze the results we conducted within subject tests examining changes in the relative importance placed on attributes under the two study contexts.

4.2. Within-subject tests

Once importance weights were obtained for each respondent, we conducted two within-subjects tests comparing the calculated importance weights as well as the rank order of attributes under the two scenarios. The first test was conducted as a paired sample *t*-test. This test, shown in Table 2, computed difference scores based on the *importance weights* assigned by each respondent to each attribute under the two scenarios presented in the study. Specifically, the paired sample difference score – d_i – was computed as respondent *i*'s importance weight for the “willingness to help” attribute under the knowledge allocation scenario minus respondent *i*'s importance weight for the “willingness to help” attribute under the knowledge retrieval scenario. The results of this test are presented in Table 2 showing a statistically significant difference in the importance weights assigned to four of the five attributes. The measurement scale for importance weights is the percentage scale, thus the value of 0.03 next to the “willingness to help” attribute in Table 2 represents a 3% increase in the importance assigned to this attribute under the allocation context versus the retrieval context. As seen in Table 2, the attributes “willingness to help” and “network ties to the respondent” were deemed more important for knowledge allocation. The attributes “self-identified expertise” and “awareness of other resources” were deemed more important for knowledge retrieval. There was no significant difference in the importance assigned to the “communication skills” attribute.

Note that the above test focuses on the importance weights assigned to each attribute rather than on the *rank order* of attributes. We conducted a second paired sample test on the ranking of attributes, using the Wilcoxon signed rank sum test, and the results are shown in Table **3**. The Wilcoxon signed rank sum test is a non-parametric test similar to a paired samples *t*-test, with the exception that it does not assume a normal distribution. In terms of the rank order of attributes, the same changes as above are seen for the attributes “willingness to help”, “network ties to the respondent”, and “self-identified expertise” but no significant difference was found for the ranking of the “awareness of others' expertise” attribute. In other words, while the importance of this attribute is reduced when considering knowledge allocation (as opposed to knowledge retrieval), its ranking has not significantly changed.

Overall the within-subject tests conducted on the data obtained through the conjoint analysis largely support our hypotheses concerning the difference in the perceived importance of the attributes in the two scenarios. We discuss the results of both studies and their contributions next.

Table 2
Results of a paired sample *t*-test of the importance weights of attributes in knowledge allocation vs. knowledge retrieval.

Attribute	Increased importance for	Mean difference (allocation − retrieval)	p-value
Willingness to help	Allocation	0.030	0.010
Communications skills	Non significant	0.000	0.493
Network ties to the respondent	Allocation	0.039	0.000
Self-identified expertise	Retrieval	−0.044	0.000
Awareness of others' expertise	Retrieval	−0.025	0.021

5. Discussion

Information technology has been proposed as a valuable tool to support expertise location in organizations, but research is needed to better understand the design of such systems. Accordingly, *the objective of this study was to explore the requirements of expertise seekers in terms of the relative importance of expert attributes used in the selection decision*. We further focused on the difference in the relative importance of attributes under different decision contexts. Specifically we examined the attributes that individuals perceive as important in allocating knowledge versus those perceived as important in retrieving knowledge. Our conjoint analysis study and subsequent within-subject comparisons of the derived importance of attributes supported our hypotheses about the relative importance of attributes for knowledge allocation and for knowledge retrieval. Utilizing the conjoint methodology which focuses on the trade-offs of attributes made by respondents, we found that when selecting a potential expert to whom knowledge will be allocated, respondents placed greater importance on their own relationships with that person, increasing the importance they assigned to the person's willingness to help and to their social ties with that person. On the other hand, when it came to knowledge retrieval, a person's expertise and awareness of others' expertise were more important.

Generalizing on our results we note that *attributes conveying the expertise of a person were perceived as more important for knowledge retrieval, whereas attributes relating to reciprocity expectations were more important for knowledge allocation*. The one attribute that was related to both expertise and reciprocity (i.e. the communication skills of the source) was perceived as equally important under both contexts.

This paper contributes toward a more effective use of IT to support expertise location and coordination in organizations. The literature so far has explored knowledge retrieval and its demands in terms of the design of information systems. In this paper we argue that expertise location and selection goes beyond knowledge retrieval and that expertise seekers may have other objectives, such as knowledge allocation. Unfortunately, much less attention has been given in the IS literature to the knowledge allocation process, even though organization members often require support in allocating knowledge. Furthermore, the transactive memory literature has identified knowledge allocation as important for the effective coordination and utilization of expertise (e.g. [18,23,34]), highlighting the need to better understand and support this process.

As a conceptual contribution, we have opened up the allocation process for future studies by showing that knowledge allocation considerations are non-trivial. In fact, our results create an important and interesting link between the allocation process and the more strategic decision of knowledge contributions and knowledge transfer, showing that people place greater importance on reciprocity attributes in the allocation context than in the retrieval context. From a practical standpoint we have demonstrated the need to customize the interface of any IT intended to support expertise location and selection by allowing its users to obtain information on task-relevant

Table 3
Results of a Wilcoxon signed rank sum test on the rank order of attributes in knowledge allocation vs. knowledge retrieval.

Attribute	Ranked higher for	p-value
Willingness to help	Allocation	0.001
Communications skills	Non significant	0.699
Network ties to the respondent	Allocation	0.003
Self-identified expertise	Retrieval	0.000
Awareness of others' expertise	Non significant	0.211

attributes as needed. Furthermore, to the extent that representing these attributes in an information system might be costly, we have provided organizations with insights on which investments are more important under different contexts.

This study is not without limitations. Most notably, we presented respondents with two specific hypothetical scenarios and only a subset of a host of potential attributes was explored. Our choice of scenarios could possibly bias the importance evaluation of specific attributes and additional scenarios should be investigated in the future. With respect to the set of attributes employed, we do not claim that this subset is better than or worse than other potential choices of attributes, but rather we show that the use of specific attributes (such as those utilized in our study) can impact expertise selection. Future work may explore additional attributes and in a more real-life decision setting. Furthermore, our survey respondents are members of a Web2.0 community and are somewhat homogenous in their knowledge sharing habits. The respondents also have many years of experience which may bias their perception of importance of some attributes, most notably network ties. However, we believe that this sample was useful for this study since the subjects possess the domain expertise needed for the conjoint analysis. Finally, our experimental scenarios involved taking knowledge from, or delivering knowledge to, a third party that may be external to the organization. In some cases one may perceive some organizational variables (such as organizational norms or organizational location) that may impact the relative importance assigned to attributes. Such factors may be investigated in future studies.

Several areas still remain unexplored. The contribution of our study can be further tested when the IT is actually implemented and the expertise selection process is carefully tracked. Studies can compare the selection of experts with and without proper IT support to identify the role played by the improved design of the IT suggested in this study. Additional attributes may be further explored to offer more insights to technology designers. While our study did not examine attributes of the expertise seeker (such as organizational tenure and expertise), future studies should examine how variations in the attributes of the expertise seeker affect their search behavior. Third, we identified “willingness to help” as an important attribute as perceived by the expertise seeker. This points to interesting issues to explore in future studies, such as the motivation behind willingness to help and whether knowledge of the specific motivation for helping may impact the expertise seekers' selection of experts. Finally, asymmetries may exist in the number of experts selected for retrieval versus allocation. For example, because of different costs involved with each process. An interesting direction for future research would be to explore how expertise seekers decide on the number of experts to include in retrieval and allocation decisions.

Appendix A. Supplementary data

Supplementary data to this article can be found online at doi:10.1016/j.dss.2012.03.005.

References

[1] A.E. Akgun, J. Byrne, H. Keskin, G.S. Lynn, S.Z. Imamoglu, Knowledge networks in new product development projects: a transactive memory perspective, Information Management 42 (8) (2005) 1105–1120.
[2] I. Becerra-Fernandez, Searching for experts on the Web: a review of contemporary expertise locator systems, ACM T on Internet Technology 6 (4) (2006) 333–355.
[3] P.M. Blau, Exchange and Power in Social Life, Wiley, New York, 1964.
[4] S.P. Borgatti, R. Cross, A relational view of information seeking and learning in social networks, Management Science 49 (4) (2003) 432–445.
[5] D.P. Brandon, A.B. Hollingshead, Transactive memory systems in organizations: matching tasks, expertise, and people, Organization Science 15 (6) (2004) 633–644.
[6] R.S. Burt, M. Knez, Kinds of third-party effects on trust, Rationality and Society 7 (3) (1995) 255–292.
[7] S.Y. Choi, H. Lee, Y. Yoo, The impact of information technology and transactive memory systems on knowledge sharing, application, and team performance: a field study, MIS Quarterly 34 (4) (2010) 855–870.
[8] R. Cross, L. Sproull, More than an answer: information relationships for actionable knowledge, Organization Science 15 (2004) 446–462.
[9] K. Ehrlich, Locating expertise: design issues for an expertise locator system, in: M. Ackerman, P. Volkmar, W. Volker (Eds.), Beyond Knowledge Management: Sharing Expertise, MIT Press, Cambridge, 2003.
[10] D. Gilmour, How to fix knowledge management, Harvard Business Review 81 (10) (2003) 16–17.
[11] P.E. Green, V.R. Rao, Conjoint measurement for quantifying judgmental data, Journal of Marketing Research 8 (3) (1971) 355–363.
[12] P.E. Green, V. Srinivasan, Conjoint analysis in marketing: new developments with implications for research and practice, Journal of Marketing 54 (4) (1990) 3–19.
[13] P.E. Green, V. Srinivasan, Conjoint analysis in consumer research: issues and outlook, Journal of Consumer Research 5 (1978) 103–123.
[14] J.F. Hair, R.E. Anderson, R.L. Tatham, W.C. Black, Multivariate Data Analysis, Prentice-Hall, Englewood Cliffs, NJ, 2009.
[15] A.B. Hollingshead, Retrieval processes in transactive memory systems, Journal of Personality and Social Psychology 74 (1998) 659–671.
[16] A.B. Hollingshead, Cognitive interdependence and convergent expectations in transactive memory, Journal of Personality and Social Psychology 81 (6) (2001) 1080–1089.
[17] Z. Huang, H. Chen, F. Guo, J.J. Xu, S. Wu, W.H. Chen, Expertise visualization: an implementation and study based on cognitive fit theory, Decision Support Systems 42 (3) (2006) 1539–1557.
[18] P. Jackson, J. Klobas, Transactive memory systems in organizations: implications for knowledge directories, Decision Support Systems 44 (2) (2008) 409–424.
[19] A. Kachra, R.E. White, Know-how transfer: the role of social, economic/-competitive, and firm boundary factors, Strategic Management Journal 29 (4) (2008) 425–445.
[20] A. Kankanhalli, B.C.Y. Tan, K.K. Wei, Contributing knowledge to electronic knowledge repositories: an empirical investigation, MIS Quarterly 29 (1) (2005) 113.
[21] D.Z. Levin, R. Cross, The strength of weak ties you can trust: the mediating role of trust in effective knowledge transfer, Management Science 50 (11) (2004) 1477–1490.
[22] K. Lewis, Measuring transactive memory systems in the field: scale development and validation, Journal of Applied Psychology 88 (4) (2003) 587–604.
[23] K. Lewis, Knowledge and performance in knowledge-worker teams: a longitudinal study of transactive memory systems, Management Science 50 (11) (2004) 1519–1533.
[24] J.J. Louviere, Analyzing Decision Making: Metric Conjoint Analysis, Sage Publications, Beverly Hills, CA, 1988.
[25] R.C. Mayer, J.H. Davis, F.D. Schoorman, An integrative model of organizational trust, Academy of Management Review 20 (1995) 709–734.
[26] D. McCullough, A user's guide to conjoint analysis, Marketing Research 14 (2) (2002) 18.
[27] D.W. McDonald, M.S. Ackerman, Just talk to me: a field study of expertise location, Proc. of the 1998 ACM Conference on Computer-Supported Cooperative Work (CSCW'98), 1998, pp. 315–324.
[28] R.L. Moreland, L. Myaskovsky, Exploring the performance benefits of group training: transactive memory or improved communication? Organizational Behavior and Human Decision 82 (1) (2000) 117–133.
[29] M.J. Muller, K. Ehrlich, S. Farrell, Social tagging and self-tagging for impression management, IBM Research technical report TR 06–02, http://domino.watson.ibm.com/cambridge/research.nsf/c9ef590d6d00291a85257141004a5c19/27658d7dcf7e8cce852572330070244d/$FILE/TR2006-2.pdf2011verified July 2011.
[30] D. Nevo, I. Benbasat, Y. Wand, Who knows what, Wall Street Journal/ Sloan Management Review, October 2009.
[31] D. Nevo, I. Benbasat, Y. Wand, Exploring meta-knowledge for knowledge management systems: A Delphi study, International Conference on Information Systems, 2003, pp. 439–449.
[32] D. Nevo, Y. Wand, Organizational memory information systems: a transactive memory approach, Decision Support Systems 39 (4) (2005) 549–562.
[33] D. Obstfeld, Social networks, the tertius iungens orientation, and involvement in innovation, Administrative Science Quarterly 50 (1) (2005) 100–130.
[34] I. Oshri, P. Van Fenema, J. Kotlarsky, Knowledge transfer in globally distributed teams: the role of transactive memory, Information Systems Journal 18 (6) (2008) 593–616.
[35] D.L. Rulke, D. Rau, Investigating the encoding process of transactive memory development in group training, Group and Organization Management 25 (4) (2000) 373.
[36] M. Ryan, S. Farrar, Using conjoint analysis to elicit preferences for health care, BMJ 320 (2000) 1530–1533.
[37] L. Terveen, W. Hill, Beyond recommender systems: helping people help each other, in: J. Carroll (Ed.), HCI in the New Millennium, Addison-Wesley, 2001.
[38] A. Tiwana, M. Keil, R.G. Fichman, Information systems project continuation in escalation situations: a real options model, Decision Sciences 37 (3) (2006) 357–391.
[39] R.W. Wang, D.M. Strong, Beyond accuracy: what data quality means to data consumers, Journal of Management Information Systems 12 (4) (1996) 5.
[40] M. Wasko, S. Faraj, Why should i share? Examining knowledge contribution in electronic networks of practice, MIS Quarterly 29 (1) (2005) 1–23.

[41] C.N. Wathen, J. Burkell, Believe it or not: factors influencing credibility on the Web, Journal of the American Society for Information Science and Technology 53 (2) (2002) 134–144.
[42] S. Watts, G. Shankaranarayanan, A. Even, Data quality assessment in context: a cognitive perspective, Decision Support Systems 48 (1) (2009) 202–211.
[43] D.M. Wegner, Transactive memory: a contemporary analysis of the group mind, in: B. Mullen, G.R. Goethals (Eds.), Theories of Group Behavior: 185–208, Springer-Verlag, New York, 1986.
[44] E.M. Whitener, S.E. Brodt, M.A. Korsgaard, J.M. Werner, Managers as Initiators of Trust: An Exchange Relationship Framework for Understanding Managerial Trustworthy Behavior. The Acad. of Management Rev. 1998, 23(3):513–530
[45] D. Yimam-Seid, A. Kobsa, Expert-finding systems for organizations: problem and domain analysis and the DEMOIR approach, Journal of Organizational Computing and Electronic Commerce 13 (1) (2003) 1–24.

Dorit Nevo is an Associate Professor of Information Systems at York University's Schulich School of Business. She received her Ph.D. in Management Information Systems from the University of British Columbia and her M.Sc. in Economics from the Technion — Israel Institute of Technology. Her current research interests include expertise location, social computing, and the impact of technology on individuals and teams.

Izak Benbasat is a Fellow of the Royal Society of Canada and CANADA Research Chair in Information Technology Management at the Sauder School of Business, University of British Columbia, Canada. He currently serves on the editorial boards of Journal Management Information Systems and Information Systems Journal. He was editor-in-chief of Information Systems Research, editor of the Information Systems and Decision Support Systems Department of Management Science, and a senior editor of MIS Quarterly. He became a Fellow of the Association for Information Systems (AIS) in 2002, received the LEO Award for Lifetime Exceptional Achievements in Information Systems from AIS in 2007, and was conferred the title of Distinguished Fellow by the Institute for Operations Research and Management Sciences (INFORMS) Information Systems Society in 2009.

Yair Wand is CANFOR Professor of MIS at the Sauder School of Business, The University of British Columbia, Canada. He received his D.Sc. in Operations Research from The Technion (Israel) and his M.Sc. in Physics from the Weizmann Institute (Israel). His current research interests include theoretical foundations for information systems analysis and design, development and evaluation of system analysis methods, and conceptual modeling. His published work includes articles in ACM Transactions on Database Systems, Communications of the ACM, IEEE Transactions on Software Engineering, Information Systems Research, Journal of Information Systems, and the Requirements Engineering Journal.