Peer-Based Computer-Supported Knowledge Refinement:

An Empirical Investigation

Kwangsu Cho  
Learning Research and Development Center  
University of Pittsburgh  
kwagsu@pitt.edu

Tingting Rachel Chung  
Katz Graduate School of Business  
University of Pittsburgh  
ting@pitt.edu

William R. King*  
Katz Graduate School of Business  
University of Pittsburgh  
billking@katz.pitt.edu

Christian Schunn  
Learning Research and Development Center  
University of Pittsburgh  
schunn@pitt.edu

* Corresponding Author
Peer-Based Computer-Supported Knowledge Refinement:

An Empirical Investigation

Knowledge management (KM) repository-based systems such as those in common use for “best practices” and “lessons learned” are generally expensive to operate since they require that expert judgment be used to determine which knowledge submissions are to be included in the system and to make refinements in the submissions to make them as efficacious as possible.

Empirical evidence has become available in cognitive psychology that suggests that experts may not be required for this “knowledge refinement” process when the consumers of knowledge are non-experts. The knowledge “distance” between experts and non-experts may make expert-centric knowledge refinement weaker. In addition, judgments by peers to the non-expert end users may substitute well for expert judgments. Multiple peer judgments, especially when they are provided through computer-supported knowledge refinement systems, may be much less costly and just as good, or perhaps even better, than expert judgments, since peers think more like the non-expert users.

A computer support system is desirable to facilitate peer-based knowledge refinement since a greater number of peers than experts are probably required for peer-based refinement to be effective. Here, we present results of both an experimental study and a corporate application that confirm the hypothesized equality or superiority of peer-based knowledge refinement in comparison to expert-centric knowledge refinement. No attempt is made to compare the actual costs of using an expert versus peers; the only issue addressed is that of comparing the quality of the two options.

Knowledge “Refineries”
Knowledge repositories are KM systems that play crucial roles in extending organizational memory, preventing organizational forgetting, and leveraging competitive advantages. When an organization solicits valuable knowledge from its employees, it becomes critically important to evaluate the submitted knowledge and refine it into a form that can be most useful for system users. A traditional assumption in the knowledge refinement process suggests that experts “provide a framework for evaluation and incorporating new experiences and information” (Davenport and Prusak, 1997, p. 5).

However, when users of a repository-based KM system are very likely to be non-experts, the knowledge selected and refined by experts may not necessarily be that which is most relevant or useful for users. For example, technical support staff usually access knowledge repository systems for topics that are unfamiliar to them. Scientists and engineers working on radical innovations often search outside their expertise domains for reusable ideas. These scientists and engineers may be experts in their own domains, but they act as non-experts when searching, and evaluating knowledge created in other domains.

**Expert-Based Refinery Processes**

Research in cognitive psychology suggests that experts and non-experts are fundamentally different in the way they represent knowledge (Chi, Feltovich, and Glaser, 1981) and solve problems (Chase and Simon, 1973). Experts possess plentiful domain-specific knowledge that is highly organized, while non-experts have loosely organized knowledge. As compared with non-experts, experts are faster in detecting problems because they require fewer cues, access their memory rather than focusing on the task at
hand, use heuristics rather than exhaustive search, recognize data patterns, and use compiled rules and response plans.

However, experts may, paradoxically, have “spectacularly narrow” views on knowledge from the non-expert user point of view. For instance, a study by Basili et al. (1996) shows that, in reading and evaluating requirements documents, better results are achieved when software developers are able to take other members’ perspectives (i.e., the testers’ and the users’) in addition to their own perspective.

One well-known expert behavior is that experts tend to underestimate the difficulty level of tasks to be performed by non-experts. Laboratory experiments demonstrate that people who know a solution to a problem tend to underestimate how difficult it would be for others to solve the same problem. Similarly, researchers have found that readers with high topic knowledge were very poor in estimating how well readers with low topic knowledge would understand a topic.

Experts also tend to overestimate the potential performance of non-experts, probably because experts detect and diagnose problems on the basis of knowledge that is readily available in their memory. Hinds (1999) showed that experts overestimated non-experts’ performance by underestimating the amount of time novices needed for task completion.

Peer-Based Knowledge Evaluation and Refinement

When non-experts code their knowledge into a form that gets refined by an expert, their knowledge differences may prevent non-experts from comprehending the results, even when the refinement is of high quality. Since experts often anchor the knowledge refinement process to knowledge that non-experts may not be able to access, such
feedback often leads to non-experts users’ misunderstanding. Moreover, explanations that are helpful to experts may not necessarily be helpful to non-experts.

Contrary to intuition, similarities among peers can actually facilitate knowledge refinement. When the intended audience is non-experts, peers often are better than experts in providing evaluations and valuable feedback on peer-developed materials. Peers are more likely to share knowledge bases, experiences, and problems, and this socially-shared cognition enables peers to establish a common ground that stimulates mutual knowledge and establishes an error correction mechanism. Because peers are closer to each other cognitively and behaviorally, they have better understandings of what they need in a codified piece of knowledge than do experts.

This apparent superiority of peers is presumably because non-experts more effectively detect or diagnose problems that are relevant to their peers. They are more accurate than experts are at understanding other non-experts’ problems because they use more cues, use more exhaustive search strategies, and do not anchor on private knowledge. These qualities are likely to make non-experts adept at coaching their peers in problem solving.

The benefit of peers can be augmented by using multiple peers. The value of multiple peers is recognized in Surowiecki’s (2004) observation that large groups of average people can make better decisions than those made by a single expert, when these people contribute diverse opinions unbiased by one another. When multiple peers participate in the refinement of knowledge, the aggregated benefits can be significant. One possible reason is that multiple peers create a larger search space for potential problems in the target knowledge. More reviewers find more problems. Also, multiple
peers can make a serious problem in the material more salient for the contributor. The probability of a serious problem being detected increases as the number of peer reviewers grows. When more than one reviewer points out the same problem, the author has more reasons to take it seriously. Moreover, multiple peers counterbalance idiosyncratic biases from individual reviewers, making the refinement process more reliable.

The Peer-Based Refinement System

Here, we describe a peer-based knowledge refinement system supported by a system developed by Cho and Schunn. Because knowledge is usually submitted in the form of a document, the system facilitates the processing of documents such as those that are submitted for consideration in a best-practice repository. First, knowledge needs are solicited, and potential authors are asked to submit knowledge, say in the form of proposed “best practices,” that they have developed for a particular procedure, method or problem. When authors submit their first drafts to the system, these submissions serve as raw materials for the refinement process. The refinement system identifies a diverse set of non-expert peers that are appropriate reviewers for each submitted draft. The contributor’s identity need not be revealed.

Peer reviewers make qualitative and then quantitative assessments of each submission on the basis of multiple criteria; in the case of this study the criteria used are — Flow, Logic, and Insight. Reviewers submit written comments on each of the dimensions; they also rate the quality of each draft on a seven-point scale. After all evaluations are collected from reviewers, the system integrates these reviews, and computes quality measures for each of the knowledge submissions, as well as the reliability of reviewer evaluations based on built-in reliability estimation algorithms. At
this point, drafts are “stamped” with these initial quality measures based on aggregated ratings that are weighted by the computed reliabilities. The system provides authors with reviewers’ comments as well as quantitative quality measures, based on which submitters revise and resubmit the knowledge document. At the same time, each contributor gets a chance to evaluate how helpful each reviewer’s feedback is in terms of refining the document.

During the last stage, reviewers from the first-round review process read the revised drafts and generate another round of written comments and ratings which the system again gathers to compute quality measures of the final drafts and reviews. In addition to evaluating these documents, the reviewers also determine whether these documents should be selected for inclusion in the repository. Again contributors assess the usefulness of these second-round reviews. Synthesizing reviewer recommendations, two rounds of reviews, and contributors’ evaluation of review quality, the system selects the most valuable documents to be stored in the repository where contributors and reviewer identities are revealed to recognize their contribution.

The Experimental Study

The empirical study simulates the knowledge refinement process in an experiment that allows us to observe the relative impact of experts versus peers on the quality of codified knowledge intended for use by non-experts. In this experiment, we compared quality improvement in technical reports refined by feedback from a subject-matter expert, a single non-expert peer, or multiple non-expert peers. The subject-matter expert was an academic scholar holding a Ph.D. degree with specialized domain expertise. The non-expert participants were 28 undergraduate students with an average of 3.4 college
years enrolled in a social science course, not taught by the expert, but covering a portion of the expert’s domain knowledge.

Individual participants wrote first and revised drafts that partially fulfilled the requirements of the course. The same participants served as reviewers and refiners and evaluated six peers’ first and revised drafts. Prior to the experiment, participants were tested on basic document generation skills. Based on the scores, participants were matched into blocks and then randomly assigned to one of three feedback source conditions: a single expert (SE), a single peer (SP), and multiple peers (MP). In the SE condition, the author received only the expert’s review. In the SP condition, the best review of the six non-expert reviews was selected and it was made available to the author. Participants in the MP condition received all six peer reviews, but not the expert review. To avoid biases, the participants were blind to reviewers’ identities and status (i.e., whether their documents were evaluated by non-expert peers or the expert) and contributors’ identity (i.e. who would receive reviewers’ feedback). The participants were told that these anonymous reviewers would solely determine the quality of their submitted documents.

About three months after the experiment, the expert re-evaluated 30% of the same documents. There was significant agreement between the expert’s first and second evaluations, showing strong test-retest reliability. A second expert then independently evaluated the expert and non-expert evaluations while being blind to the source of evaluations and showed a statistically significant correlation with the expert.

After being assigned to experimental “treatments,” the participants were introduced to the system by their course instructor. All of the remaining procedures were
managed online by the system. On the system’s prompt, all participants submitted their first drafts online by the same date. Then, each participant received six drafts that were randomly selected by the system. At the same time, the expert reviewed all of the drafts. The expert and non-expert reviewers assessed the drafts on the three evaluation dimensions: Flow (concerns document readability, emphasizing organization and overall composition), Logic (evaluates the degree to which arguments presented in the document are supported by evidence), and Insight (measures if the document provides innovative ideas that indicate creativity).

Even though each document received expert and six peers’ reviews, only some of those reviews were made available to each submitter, depending on the experimental condition. After receiving feedback, each participant submitted revised drafts, evaluated the helpfulness of the feedback, and then received the second reviews on the revised drafts. Contributor evaluations of these reviews were not available to the reviewers.

Results of the Experiment

The differences in the impact of expert-based versus peer-based knowledge refinement were assessed using a two-way mixed ANOVA on quality improvement from first to second drafts measured by expert evaluations. As shown in Figure 1, simple main effect analyses reveal that Flow in MP is significantly better than that in SE and SP, that Logic is the same across all conditions, and that Insight in MP is significantly better than that in SE. In other words, documents reviewed by multiple peers undergo significant quality improvement on both Flow and Insight. These results support the hypothesis that knowledge distance between experts and non-experts may hinder knowledge refinement, and the hypothesis that knowledge refinement benefits from multiple peer feedback. The
effect is particularly strong on the Insight dimension, suggesting that multiple peer
reviews are likely to stimulate creative ideas. In addition, Figure 2 shows that novices
evaluated expert and novice feedback to be equally helpful, while experts evaluated
expert feedback to be more helpful than novice feedback, suggesting that when the target
audience is novice users, novice refiners are just as helpful as expert evaluators are.
Interestingly, experts do think expert feedback is more helpful than novice feedback.

The Real-World Application

These experimental findings suggesting that peer reviews may be equal or
superior to expert reviews we verified with data collected from an IT consulting firm in
Korea that implemented a procedure that enabled peer-expert comparisons in their
customer service process. Customers were asked to evaluate (“thumbs up/satisfactory” or
“thumbs down/unsatisfactory”) answers provided by customer service representatives.
Answers to customer questions in an existing database were written either by expert
designers or programmers. Out of 245 answers, 134 (55%) were refined by peers and 111
(45%) were refined by experts before customers received responses. Among the 162
(66%) that were rated by customers, 116 (71 %) were voted to be satisfactory and 28 (46
%) were unsatisfactory. As shown in Figure 3, 79 % of the peer-refined responses were
satisfactory, whereas only 62% of the expert-refined responses were satisfactory. In
contrast, 21% of the peer-refined responses were unsatisfactory, whereas 38% of the
expert-refined responses were unsatisfactory. These differences are statistically
significant and give further credibility and generalizability to the results of the prior
experiment.

Discussion of Results
This study represents one of the first attempts to empirically investigate properties of the knowledge refinement process in KM. The results show that as hypothesized, the knowledge “distance” between experts and non-experts made expert-based knowledge refinement impaired, while the close knowledge distance among peers facilitated knowledge refinement.

Considering experts rarely work without stringent time constraints, expert-based knowledge refinement may be worse. Experts under time pressure often default to typical expert behaviors, such as using fewer cues than non-experts do to build task representations. They do so by activating existing task schemata in memory. Because experts rely more on their expert instincts under time pressure, they may be even less likely to take the time to consider the non-expert’s perspective.

Computer-supported peer review systems offer what may be a more financially affordable option. Contributors and reviewers may be rewarded for their services through the publishing of their names when their knowledge is selected for inclusion in the repository. Thus, both enjoy substantial social rewards. This was observed in an informal knowledge repository in a software development firm (Dingsoyr and Roeyvik, 2003) and is a well-known characteristic of the Linux virtual development team (Lee and Cole, 2003). Over time, such a repository enables a reputation system to develop that helps users preliminarily assess likely knowledge relevance and quality. A similar reputation system at the group level has successfully directed user attention to high quality content in an electronic document database (Hansen and Haas, 2001).

When the peer-based knowledge-refinement process helps users assess content quality, it should gradually build trust as a result of the creation of a virtual community.
When a large number of documents are available in such a repository, the system represents a knowledge market that competes for the reader’s limited attention (Hansen and Haas, 2001). Systems allowing users to inspect feedback from other users may help maintain trust in the repository in a way similar to that online merchants such as Amazon.com use to establish consumer trust through a peer feedback mechanism.

The system used here makes it feasible for organizations to establish a reward system for both knowledge codification and refinement. Extrinsic incentives as well as social reputation reward may be used to motivate employees to participate in knowledge refinement. When employees are involved and rewarded in the process, they may be more likely to use knowledge from the repository system for their own tasks. These benefits may explain the success of peer reviews reported in trade magazines, such as software pattern writers’ reliance on peer discussions in the process of writing up patterns.
Figure 1

Quality improvement with standard error bars
Figure 2

Expert and Novice Perception on Expert and Novice Feedback
Figure 3.

Customers satisfaction ratings of answers refined by experts and by peers
References


Surowiecki, J. (2004). *The wisdom of crowds: why the many are smarter than the few and how collective wisdom shapes business, economies, societies and nations*. Doubleday.