Yang, S. J. H., Chen, I. Y. L., Kinshuk & Chen, N.-S. (2007). Enhancing the Quality of e-Learning in Virtual Learning Communities by Finding Quality Learning Content and Trustworthy Collaborators. *Educational Technology & Society*, 10 (2), 84-95.

Enhancing the Quality of e-Learning in Virtual Learning Communities by Finding Quality Learning Content and Trustworthy Collaborators

Stephen J. H. Yang
Dept of Computer Sc and Information Engg, National Central University, No.300, Jung-da Rd. JhongLi, Taiwan, 320
Tel.: +886-3-4227151-35308 // Fax: +886-3-4222681
jhyang@csie.ncu.edu.tw

Irene Y. L. Chen
Department of Information Management, Ching Yun University, No.229, Chien-Hsin Rd., Jungli, Taiwan, 320
Tel.: +886-3-4581196 ext 7319 // Fax: +886-3-4683904
irene@cyu.edu.tw

Kinshuk
School of Computing and Information Systems, Athabasca University, Canada
Tel: +1-780-675-6812 // Fax: +1-708-675-6148
kinshuk@ieee.org

Nian-Shing Chen
Dept of Information Management, National Sun Yat-Sen University, No. 70 Lien Hai Rd., Kaohsiung, Taiwan
Tel: +886-7-5252510 // Fax: +886-7-5254799
nschen@cc.nsysu.edu.tw

ABSTRACT

Virtual learning communities encourage members to learn and contribute knowledge. However, knowledge sharing requires mutual-trust collaboration between learners and the contribution of quality knowledge. This task cannot be accomplished by simply storing learning content in repositories. It requires a mechanism to help learners find relevant learning content as well as knowledgeable collaborators to work with. In this paper, we present a peer-to-peer based social network to enhance the quality of e-learning regarding knowledge sharing in virtual learning communities. From a technical viewpoint, we will present advanced semantic search mechanisms for finding quality content and trustworthy collaborators. From the social viewpoint, we will address how to support a trustworthy social network that encourages learners to share. Results of this research demonstrate that applying such mechanisms to knowledge sharing can improve the quality of e-learning in virtual learning communities.

Keywords

Quality of e-learning, quality content, trustworthy, knowledge sharing, virtual learning community

Introduction

The explosion in web-based technology has led to increasing volume and complexity of knowledge, which stimulates the proliferation of virtual learning communities (VLCs). VLCs are information technology-based cyberspaces in which individuals and groups of geographically dispersed learners accomplish their goals of e-learning. One of VLCs' purposes is to encourage knowledge sharing so that valuable knowledge embedded in the network can be effectively explored. Most of the learners participate in VLCs with the expectations that they can acquire and share valuable knowledge to suit their needs.

The emergence of VLCs over the past decade has stimulated research interests by academia and practitioners. Bruckman (2002) found that the learning potential of the Internet technology can come from peers and elders. Jin (2002) provided a conceptual framework for the development of a prototype system of the virtual community-based interactive learning environment. Wachter et al. (2000) pointed out that an enhanced learning environment is possible only if one goes beyond mere online course delivery and creates a community of learners and other related resource groups. Wasko and Faraj (2005) found that knowledge sharing has been a motivation for participation in virtual communities. In addition, many web-based or agent-based models and software have been proposed to support interaction, discussion, and collaboration in VLCs (Taurisson & Tchounikine, 2004; Zhang & Tanniru, 2005; Matusov, Hayes, & Pluta, 2005; Avouris, et al., 2004). Prior studies have provided evidence that demonstrates the importance of knowledge exchange in enhancing learning performance. They also have called for the attention of providing mechanisms to support knowledge sharing in VLC environments.

However, knowledge sharing in some VLCs has not lived up to expectations. Two barriers preventing efficient and effective knowledge sharing are: (1) the difficulty in finding quality knowledge, and (2) the difficulty in finding trustworthy learning collaborators to interact with.

The objective and contribution of this research is applying peer-to-peer (P2P) based social networks with trust-management mechanisms to overcome the aforementioned barriers. In order to help learners find quality content and trustworthy collaborators, we provide peer-ranking mechanisms and classify peers based on their content's quality. We have enhanced the typical keyword search with a keyword thesaurus search and a semantic search to improve the performance of content discovery. We have also enhanced conventional online group discussions by finding trustworthy collaborators who are more willing to share.

Finding relevant and quality learning content

One of the motivations for participating VLCs is knowledge sharing. Without high-quality content, a VLC cannot achieve its intended purpose of encouraging knowledge sharing. The information areas for course materials, discussion forums, newsletters, and recommended articles in a VLC's website constitute its knowledge/experience repository. Whether learners can effectively explore and exploit the knowledge within a VLC significantly influences the extent to which knowledge sharing can be achieved. High-quality content can attract learners to participate in the knowledge activities and continually add to and enrich the knowledge in the repository, which in turn, facilitates knowledge sharing.

Knowledge domain and quality control

To facilitate content resource management, we classify resources based on their knowledge domains and their quality. We utilize ACM Computing Classification System 1998 (http://www.acm.org/class/1998/) as our classification base for knowledge domains. In order to organize and provide better resource management, each peer in our P2P network needs to classify content and evaluate the quality of content based on their reputation, number of times the site is accessed per day, and the matching degree by which the content classification conforms to the knowledge domain. The quality of resource *i* in knowledge domain *j* is given as

$$QoR_{(i,j)} = REP_{(i,j)} \times TOA_i \times MD_{(i,j)}$$

where:
QoR: quality of a content resource
REP: reputation represents the rating of the resource, the higher it is, the better the reputation is.
TOA: the total number of times a resource has been accessed per day. TOA represents the degree of popularity, the higher it is, the more popular it is.

MD: the matching degree of how a content classification conforms to knowledge domain, the higher it is, the better the match.

The quality of a peer with respect to a certain knowledge domain, *j*, is the summation of the quality of resource,*i*, over the number of content resources, as given below:

$$QoP_j = \frac{\sum_{i=1}^{NoR} QoR_{(i,j)}}{NoR}$$

where
QoP: quality of a peer
NoR: the number of content resources, which represents the volume of content in a peer.

The quality of a peer with respect to all knowledge domains contained in this peer is the average of QoP_j, which is given as follows:

$$QoP = \frac{\sum_{j=1}^{NoD} QoP_j}{NoD} \quad = \quad QoP = \frac{\sum_{j=1}^{NoD}\left(\frac{\sum_{i=1}^{NoR}(REC_{(i,j)} \times TOA_i \times MD_{(i,j)})}{NoR}\right)}{NoD}$$

where
NoD: number of knowledge domains, which represents the scope of this peer.

P2P-based content search

Based on the content classifications and their quality control, we now present our P2P environment and illustrate how to use it to find more relevant quality content. We have constructed a P2P environment, as shown in Figure 1. Each peer in our P2P environment consists of two modules: Resource Module and Search Module. The Resource Module is designed to formally describe resources contained in a peer. The Search Module is responsible for generating user's search query and processing search requests received from other peers.

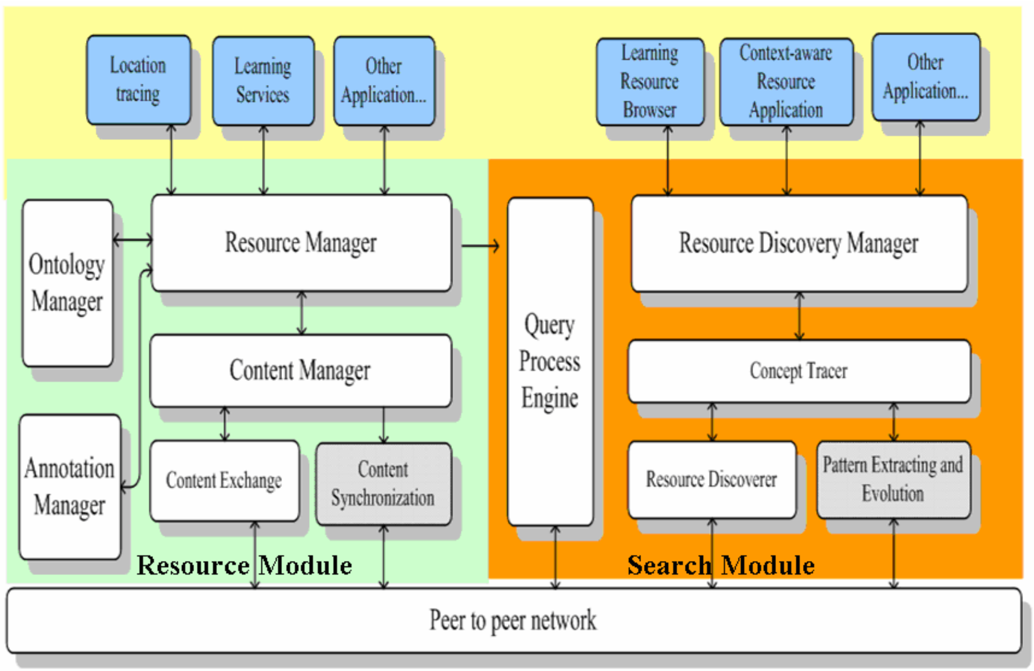

Figure 1. System architecture of peer-to-peer network

The Resource Module contains several managers to organize and manage the resources kept in the peer. The Resource Manager is the coordinator that handles all kinds of resources from various managers. These resources can be learning content, learning services, or other applications provided by the peer. The managers include the Content Manager (which handles the content repository), the Ontology Manager (which provides semantic metadata of contents), and the Annotation Manager (which processes annotation imposed onto the content).

The Search Module contains a Query Process Engine and a Resource Discovery Manager. The Query Process Engine is an interface designed to generate search requests. If users cannot specify their search request clearly, the Query Process Engine automatically generates one for users based on the surrounding context. The Resource Discovery Manager is designed to process search requests received from other peers by providing a concept map to guide the searching process. The concept map is derived from the keyword dictionary and keyword thesaurus terms based on users' requests; the concept map is extended or redrawn to match users' search requests.

We have enhanced and implemented P2P in our previous research (Yang, Chen, & Shao, 2004; Yang 2006). For content discovery, our P2P provides the functions of a basic keyword search, keyword thesaurus, and concept map-based search. Based on the content classifications and their quality control, the keyword thesaurus is used to extend search scope by finding more relevant keywords. In contrast, the concept map-based search is used to derive a more precise search scope by finding the most relevant keyword.

As shown in Figure 2, the basic keyword search is enhanced by a keyword thesaurus. Our P2P matches not only a single keyword but also a set of related keywords previously classified and saved in our content repository. The search results are shown in the main window along with resource's file name, type, size, state, and rating. For example, a keyword search of "New York Vacation" will generate a keyword thesaurus, providing terms such as "New York City Life," "New York Travel," and even "New York Yankee."

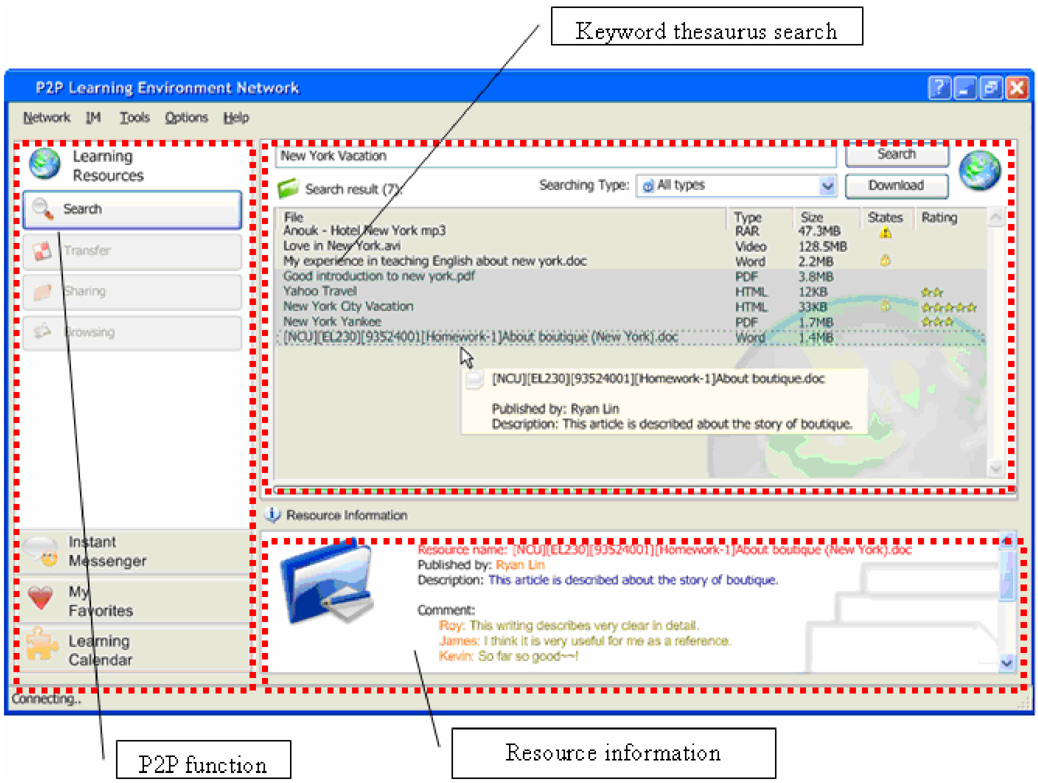

Figure 2. P2P network with keyword thesaurus search

For a semantic search, we use the concept-map approach to construct the relationship of a keyword concept and its related concept (Chau, & Yeh, 2004). For example, if a user inputs the concept "web services," the system will prompt a concept map with three nodes and two edges. One edge connects from web services to Semantic Web, and the other connects from web services to DAML-S. If the user continues to press the node"Semantic Web," the concept map will grow closer to the one shown in Figure 3. If the user then double-clicks the node "XML," the system will proceed to do the search and generate the results. In the upper left window of Figure 3 is the description of the concept. The lower left window shows the types of resources and their abstracts related to the concept, and the lower right window shows detailed information regarding the resource selected from the lower left window.

Finding trustworthy and socially related learning collaborators

Social-interaction ties are the structural links created through the social interactions among individuals in a network (Burt, 1992; Putnam, 1995; Wasko, & Faraj, 2005; Zhang, Jin, & Lin, 2005). Previous studies suggest that an individual's centrality in an electronic network of practice can be measured using the number of social ties an individual has with others in the network (Ahuja et al., 2003). Some academics addressed the importance of social interaction ties in knowledge exchange. For example, Tsai and Ghoshal (Tsai, & Ghoshal, 1998) found that social-interaction ties have positive effects on the extent of inter-unit resource exchange. Wasko and Faraj (2005) found that the centrality built up by the social-interaction ties that any individual creates in a network significantly and positively impacts the helpfulness and volume of knowledge contribution.

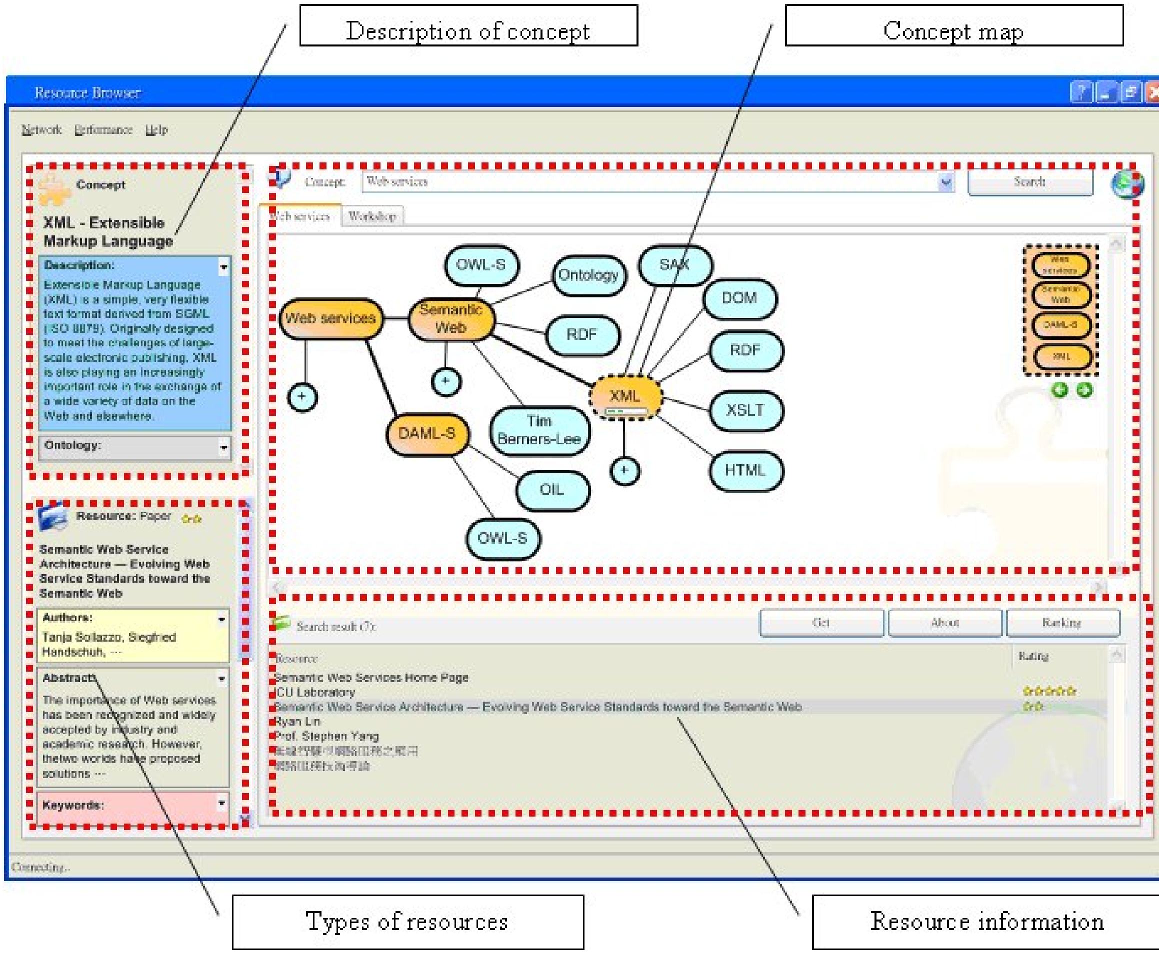

Figure 3. P2P with concept map

The Internet enables knowledge sharing in ways that were not possible before, such as through online group discussions. It also gives rise to virtual learning communities (VLCs), which enable knowledge exchange without any physical meeting among the participating members. A virtual learning community is a special kind of virtual community that aims to enhance learning performance. VLCs provide an interactive environment of mutual sharing and learning. The objective of knowledge management in VLCs is to facilitate exploitation and exploration of knowledge. Therefore, the learning process in such environments involves intensive online knowledge sharing between learning collaborators: the learners (consumers) and the contributors (producers) of knowledge.

A VLC's knowledge has both explicit and implicit components. The explicit knowledge can be easily browsed over the Internet, yet its implicit knowledge resides in the heads of the community members themselves and is shared with others through social interaction. Posting and responding to messages creates a social-interaction tie between learners. The more social interaction ties a learner has, the more easily he/she may acquire or share relevant knowledge. Therefore, social-interaction ties are positively associated with knowledge quality in a virtual learning community.

P2P-based social network support

The term social network (Upadrashta, Vassileva, & Grassmann, 2005; Wellman, 1997) is used to describe a learner's social relationship with other learners in a VLC. We implement a hierarchical P2P-based social-network support for knowledge sharing. As shown in Figure 4, a P2P knowledge network (K-network) is established to connect active learners within a pool of active peers, i.e., the learners (peers) that are online and available through the Internet. The pool can be an entire P2P network or a specific virtual community. Each peer (e.g., a ~ f) in Figure 4 represents a knowledge repository or a knowledgeable individual.

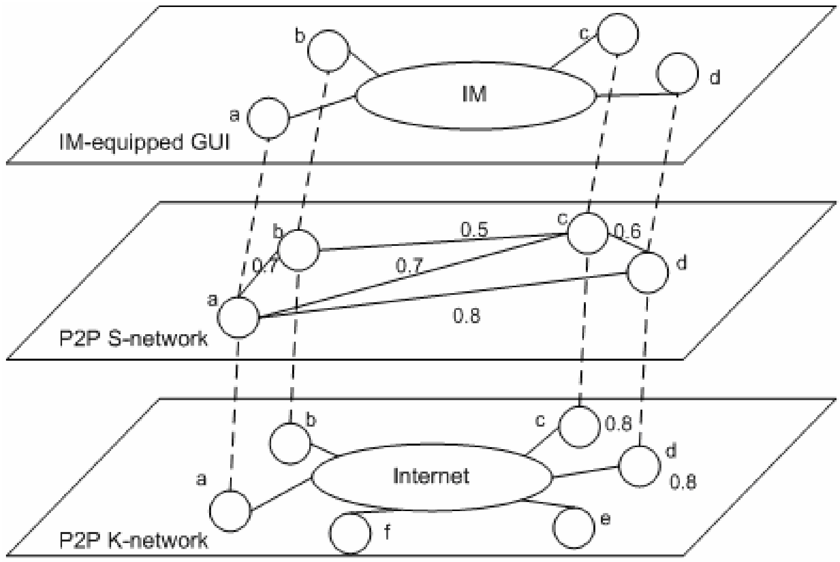

Figure 4. P2P-based social network support for knowledge sharing

If a peer in a P2P K-network, e.g., peer *a*, requests a specific piece of knowledge, the social-network support will dynamically generate a P2P S-network based upon the requester's social relationships with other peers who own the requested knowledge. As shown in Figure 4, peers that do not know about the relevant knowledge are filtered out and will not appear on the P2P S-network (e.g., peers *e* and *f*). Weighted edges in the generated S-network are called trust association (TA) to represent the levels that the peers can help the requester (peer *a*). Based on the example shown in Figure 4, peer *d* is more trustworthy than peer *c* because the TA between peers *a* and *d* is 0.8, which is greater than the TA between peers *a* and *c*, which is 0.7. Based upon the generated S-network, an IM-equipped (instant messenger) Graphical User Interface (GUI) is created to help the requester interact with other peers in real time.

The essential technique in such social-network support is how to construct a social network with trustworthy collaborators. The construction of such a social network is mainly based upon calculations of social-network association between peers in the P2P environment. Each pair of peers is associated with two kinds of association—trust association and knowledge association, which will be addressed in the following subsections.

Trustworthy social networks

The concern of trustworthiness in a social network can be classified into three levels—infrastructure, understanding, and policy. Infrastructure, the first level, focuses on keeping a trusted infrastructure. For example, the underlying software and hardware of a web-based VLC must be trustworthy. The network should guarantee that network transmission is reliable and secure.

Understanding is the second level of trustworthiness. Huhns and Buell (2002) pointed out that we are more likely to trust something if we understand it. One needs to confirm with confidence the things he/she requested. One approach is to analyze experiences and estimate the degree of trust based on one's past experiences (Singh, 2002), such as rating services, reputation mechanisms, and referral networks for exchanging experiences and reputation based on a third-party certification group (Grandison, 2000) or a peer-to-peer sharing mechanism (Yolum and Singh, 2002).

Policy, the third level of trustworthiness, is used to describe requirements of trust, security, privacy, and societal conventions to reach high-level trustworthy objectives (Huhns, 2002; Singh, 2002). In general, the policy provides many specific description - methods to enable the requesting party to define what states and situations it could accept. In other words, policy works as a set of rules to decide what behaviors and states could acquire authorizations. In this paper, we present an experience-based evaluation of learners' trustworthiness based on understanding and policy levels.

Calculation of trust association

Trust association is a measure of how two peers (learners) on the social network treat each other. It also indicates how a learner is associated with other learners directly connected to her on the social network. For a pair of learners who are socially related, as denoted by the requesting learner *i* and the requested learner *j*, the trust association between the two learners is denoted by TA(i,j). TA(i,j) indicates the level of trustworthiness of the requesting learner *i* to the requested learner *j*. TA(i,j) is used to determine whether the requested learner conforms to the requesting learner's requirements of trustworthiness. The value of TA(i,j) is denoted by a percentage. The higher the percentage of confidence, the higher the trust association. For example, if the value of TA(Chris, Albert) is 78%, which means the requesting learner Chris has 78% confidence that the requested learner Albert is trustworthy.

We utilize sampling of binomial probability to calculate the value of TA(i,j), based on a 95% confidence interval in terms of probability (Mitchell, 1997). We first define the following terms:

- S is a set of interaction instances representing samples of the requested learner's past interactions, $S = \{s_1, s_2, \ldots s_n\}$.
- Tr is a set of trust evaluation values containing past experience instance, and is denoted by $Tr = \{tr_1, tr_2, \ldots tr_n\}$.
- $Rating: S \rightarrow Tr\ Rating(s)$: The Rating function maps the interaction instance s to past experience instance, tr. In other words, the function associates past service instance with past experience instance, the experiences are collected by learners other than the requesting learner.
- $Accpet: Tr \rightarrow \{0,1\}$ A requirement hypothesis can be denoted as $Accpet$ function. The output of Accept function is 1 when past experience instance is accepted by the requesting learner, otherwise is 0.

$$\mathrm{Accpet}(\mathrm{tr}) \equiv \begin{cases} 1 & \text{Accept} \\ 0 & \text{otherwise} \end{cases}$$

Based on the usage of LargeSample of Hypothesis for a Binomial Proportion to evaluate the simple error and true error of a hypothesis addressed in (Mitchell, 1997; Mendenhall, 1999), the result of the hypothesis assesses that the sample is a Boolean value (true or false). Thus we can see that the hypothesis assesses the sample as a Bernoulli trial, and the distribution of the Bernoulli trial is a binomial distribution. The binomial distribution approximates the normal distribution when there are large enough samples. Simple error is the correct rate in samples, and true error is the correct rate in population. We will get a confidence interval according to the simple error. The area of confidence interval represents a probability in which true error falls. In normal distribution, the true error is when 95% of the resultsfall within the range of $mean \pm 1.96 \times SD$ (Standard Deviation) in compliance with the experience rule. In other words, we can utilize the confidence interval to evaluate lowest true error of the evaluating hypotheses.

Let $Accpet$ function be the hypothesis, and then we can evaluate the possible true error of the hypothesis based on the past instances S according to the Evaluating Hypotheses Theory (Mitchell, 1997). Whether the tr ($tr \in E$) is accepted by $Accpet$ is a binomial distribution which approximates the normal distribution when the number of samples is large enough. Thus we can utilize the normal distribution to ensure that the sample error closes with the true error. The true error occurs when 95% of probabilities fall within a confidence interval, which will be approved as a trustworthy learner in the general application.

We define the confidence symbol as the lowest bound of the true error. The trust of service conforms to the request's requirement when the confidence is higher.

$$\hat{p} = \frac{1}{n}\sum_{s \in S} Accpet(Rating(s)),\ SD = \sqrt{\frac{\hat{p} \times (1-\hat{p})}{n}},\ z_{95\%} = 1.96$$

$$Confidence \equiv \max\{\hat{p} - z_{95\%} \times SD, 0\}$$

As the number of samples increases, the standard deviation decreases relatively, and the confidence will be closer to the true error. For example, the past instances of a requested learner are denoted as S, and let $|S| = 256$. The requesting learner proposes a Requirement Hypothesis $Accpet$. If the result of the calculation is $\hat{p} = 0.6$, the confidence can be calculated from the following equation:

$$\hat{p} = \frac{1}{256}\sum_{s\in S} Accpet\big(Rating(s)\big) = 0.6\,,\; z_{95\%} = 1.96$$

$$Confidence = \hat{p} - z_{95\%} \times \sqrt{\frac{\hat{p}\times(1-\hat{p})}{256}} \cong 0.6 - 0.060012 = 0.539987$$

The calculated confidence, i.e., TA(i,j) is 53.99%, which means the requesting learner has 53.99% confidence that the requested learner can meet the trustworthy requirement based on 95% confidence interval. Hence, we can assert that the trustworthiness of the requested learner is 56.83% (53.99% over 95%) conforming to the requesting learner's requirements.

Calculation of knowledge association

Learners' knowledge association can be described by learners' domain of knowledge along with their proficiency pertaining to the corresponding domain. We use the ACM Computing Classification System to classify domain of knowledge, and use Bloom's taxonomy matrix (Benjamin, 1956; Anderson, 2001) to classify learners' proficiency in that domain. As shown in Figure 5, the Bloom taxonomy matrix consists of two dimensions, the knowledge dimension and the cognitive process dimension. Each cell in the matrix is associated with a value ranging between 0 and 1, indicating the level of proficiency. For example, given a learner with a Bloom's taxonomy matrix rating, as shown in Figure 5, indicates the learner is good at memorizing and understanding factual and procedural knowledge pertaining to the corresponding domain.

	Cognitive Process Dimensions					
Knowledge dimension	Level 1 Remember	Level 2 Understand	Level 3 Apply	Level 4 Analyze	Level 5 Evaluate	Level 6 Create
A. Factual knowledge	0.9	0.8	0.4	0.4	0	0
B. Conceptual knowledge	0.3	0.3	0.3	0.1	0	0
C. Procedural knowledge	0.6	0.5	0.3	0.2	0	0
D. Metacognitive knowledge	0	0	0	0	0	0

Figure 5. Example of the Bloom taxonomy matrix

Let a learner in a P2P K-network request for a specific piece of knowledge *k* with proficiency, denoted by a Bloom taxonomy matrix, $BT_{(k)}$. Whether a learner *i* conforms to the request of learner *i* is computed by:

$$KA_k(i) = KP_k(i) \bullet (BT_{(k)}(i))$$

where

$KA_k(i)$: The knowledge association of a learner, *i*, with respect to a certain domain of knowledge, *k*. $KA_k(i)$ is a Bloom taxonomy matrix.

$KP_k(i)$: The knowledge proficiency of a learner, *j*, with respect to a certain domain of knowledge, *k*. $KP_k(i)$ is a Bloom taxonomy matrix.

$BT_{(k)}(i)$: A learner, *i*, requesting a specific piece of knowledge, *k*, with proficiency, $BT_{(k)}$. $BT_{(k)}(i)$ is a Bloom taxonomy matrix.

The matrix notation of KA can be further serialized into a single value by the following:

$$KA_k(i) = \sum_{m=1}^{4}\left(\sum_{n=1}^{6} KA_{(m,n)}\right)$$

For example, a learner, *i*, is requesting learners with the proficiency to apply conceptual knowledge of *Software Engineering* to solve problems. Based on the aforementioned equation, this request can be denoted as:

$$BT_{SE}(i)=\begin{bmatrix}0&0&0&0&0&0\\0&0&1&0&0&0\\0&0&0&0&0&0\\0&0&0&0&0&0\end{bmatrix}$$

$$KA_{SE}(i)=KP_{SE}(i)\bullet(BT_{(SE)}(i))$$

$$KA_{SE}(i)=\begin{bmatrix}0.9&0.8&0.4&0.4&0&0\\0.3&0.3&0.2&0.1&0&0\\0.6&0.5&0.3&0.2&0&0\\0&0&0&0&0&0\end{bmatrix}\bullet\begin{bmatrix}0&0&0&0&0&0\\0&0&1&0&0&0\\0&0&0&0&0&0\\0&0&0&0&0&0\end{bmatrix}$$

$$KA_{SE}(i)=\begin{bmatrix}0&0&0&0&0&0\\0&0&0.2&0&0&0\\0&0&0&0&0&0\\0&0&0&0&0&0\end{bmatrix}$$

After the serialization of $KA_{SE}(i)$, $KA_{SE}(i)=0.2$

Calculation of social network association

Based on the aforementioned calculations of trust association (TA) and knowledge association (KA), we now proceed to calculate the social network association (SNA) as following:

$$SNA_k(i,j)=KA_k(j)\times TA(i,j)$$

where

$SNA_j(i,j)$ *: Network association between learner i and learner j concerning a specific domain, k*

$KA_k(j)$ *: knowledge association of learner j concerning a specific domain, k*

$TA(i,j)$ *: trust association between learner i and learner j*

Using the example shown in Figure 4, if learner "*a*," is requesting a specific piece of knowledge, learner "*d*" can be more helpful than learner "*c*" because the value of $NA_k(a,d)$ is higher than the value of $NA_k(a,c)$.

$KA_k(c)=0.8$
$TA(a,c)=0.7$
$NA_k(a,c)=0.8*0.7=0.56$

$KA_k(d)=0.8$
$TA(a,d)=0.8$
$NA_k(a,d)=0.8*0.8=0.64$

Experiments and discussion

We have conducted quantitative and qualitative experiments to evaluate the mechanisms and environments presented in this paper. To evaluate the performance of finding quality content via our P2P network, we measured two important indexes, Precision and Recall, and demonstrate that, by using content classification with peer ranking and quality control presented in this paper, our keyword thesaurus and concept map do outperform conventional keyword searches.

Consider a request of document search and its set of relevant documents, and let $|R|$ be the number of documents in this set. Assume that a given search method generates a retrieved set of documents, and let $|A|$ be the number of documents in this retrieved set. Let $|Ra|$ be the number of documents in the intersection of sets R and A. Precision is defined as $Precision = |Ra| / |A|$, which is the proportion of retrieved documents that are considered relevant. Recall is defined as $Recall = |Ra| / |R|$, which is the proportion of relevant documents that have been retrieved. We compared the three search methods, keyword search, keyword thesaurus, and concept map on their search results of five knowledge domains as defined in ACM Computing Classification System, 1998 Version. The results of the experiment are shown in Table 1.

Table 1. Three search methods and their search results of five knowledge domains

	Keyword search		**Keyword thesaurus search**		**Concept map search**	
domain knowledge	Precision	Recall	Precision	Recall	Precision	Recall
e-learning	0.443	0.567	0.814	0.733	0.714	0.833
mobile learning	0.467	0.400	0.633	0.511	0.433	0.600
pervasive learning	0.367	0.443	0.600	0.429	0.541	0.729
ubiquitous learning	0.367	0.450	0.684	0.450	0.431	0.750
situated learning	0.375	0.345	0.645	0.316	0.545	0.716

As indicated in Table 1, for the five given knowledge domains, the Precision of a keyword-thesaurus (KT) search shows better performance than the other two search methods. This indicates that the retrieved contents are mostly relevant because the retrieved documents are the search results for relevant keywords. For the five given knowledge domains, the Recall of a concept map (CM) search shows better performance than the other two search methods. This indicates that most of the relevant content associated with a concept can be retrieved because the search results are based on the main concept and its derived concepts on the concept map.

In addition to the quantitative performance analysis, to evaluate the performance of our P2P-based social network support, we have conducted a qualitative experiment with 56 undergraduate computer-science major students (juniors) enrolled in a class entitles, "Introduction to Knowledge Engineering." All students were required to use the P2P networks and the social network support presented in this paper. Items in the questionnaire were measured based on a five-point Likert scale ranging from (1), "strongly disagree," to (5), "strongly agree." The results of survey items are shown in Table 2.

Table 2. Performance of P2P-based social network support

No.	**Questionnaire**	**Mean**	**SD**
1	Do you think the found collaborators are knowledgeable?	4.24	1.13
2	Are you confident the found collaborators are trustworthy?	4.37	0.78
3	Do you think you can find better collaborators compared with the P2P social network support?	4.56	1.10
4	Are you satisfied with the user interface design?	3.95	0.94
5	Is it easy to form a group discussion by using the support?	3.67	1.28
6	Are you satisfied with the system performance in terms of communication and synchronization?	3.56	0.84
7	Do you think it is important to connect this support to other instant messengers?	4.23	0.62
8	Do you think it is important to have voice-enabled support?	4.37	0.68
9	Do you think it is important to have an e-whiteboard for synchronous file sharing?	4.18	0.61

Table 2 shows that most of the collaborators found by this P2P social network support are knowledgeable and trustworthy. Nevertheless, learners still prefer to choose their own partners even though they thought the collaborators found by the system were knowledgeable and trustworthy. This observation suggests that we need to take into account learners' social relationships in addition to their knowledge competence. Most of the learners thought that the user interface design is very important, and they wished that they could have better control regarding choosing collaborators. We also found that learners wanted to connect to other instant messengers and demanded many real-time functions while they were interacting with other collaborators via voice communication and e-whiteboard for synchronous discussion and file sharing.

Concluding remarks and future research

The objective and contribution of this paper is to apply social networks to enhance the quality of e-learning regarding knowledge sharing in virtual learning community by overcoming two barriers: difficulty in finding quality knowledge and difficulty in finding trustworthy learning collaborators. The results of this research demonstrate that applying such mechanisms to knowledge sharing do improve the quality of e-learning in virtual learning communities. We provide several avenues for further research. It is a general problem in social networks to support the discovery, access, and sharing of knowledge. Further study is needed to investigate the special requirements from different learning contexts in virtual learning communities, such as, for a given time, where are the learners? Who are the learners with? What are the learners doing? And what resources are available for learners? We will consider such context-aware learning in our future research.

Acknowledgements

This work is supported by National Science Council, Taiwan, under grants NSC 94-2524-S-008-001 and NSC 95-2520-S-008-006-MY3.

References

Ahuja, M., Galletta, D., & Carley, K. (2003). Individual centrality and performance in virtual R&D groups: An empirical study. *Management Science*, 49(1), 21–38.

Anderson, L. W., Krathwohl, D. R., Airasian, P. W., Cruikshank, K. A., Mayer, R. E., Pintrich, P. R., Raths, J., & Wittrock, M. C. (2001). A taxonomy for learning, teaching, and assessing: A revision of Bloom’s taxonomy of educational objectives, New York: Longman.

Avouris, N., Komis, V., Margaritis, M., & Fiotakis, G. (2004). An environment for studying collaborative learning activities. *Educational Technology & Society*, 7 (2), 34–41.

Benjamin S. (1956). *Bloom’s Taxonomy of Educational Objectives*, *Handbook 1: Cognitive Domain*. New York: Longmans Green.

Bruckman, A. (2002). The future of e-learning communities. *Communications of the ACM, 45* (4), 60–63.

Burt, R. S. (1992). *Structural Holes: The Social Structure of Competition*. Cambridge, MA: Harvard University Press..

Chau, R., Yeh, C. H. (2004). Fuzzy conceptual indexing for concept-based cross-lingual text retrieval, *IEEE Internet Computing*, 8(5), 14–21.

Grandison, T. & Sloman, M. (2000). A survey of trust in Internet applications. *IEEE Communications Surveys,* 2–16.

Huhns, M. N. & Buell, D. A. (2002). Trusted autonomy. *IEEE Internet Computing*, 92–95.

Jin, Q. (2002). Design of a virtual community-based interactive learning environment. *Information Sciences*, 140(1–2), 171–191.

Matusov, E., Hayes, R., & Pluta, M. J. (2005). Using discussion webs to develop an academic community of learners. *Educational Technology & Society*, 8 (2), 16–39.

Mendenhall, W. & Beaver, R.J. (1999). Introduction to probability and statistics. *Duxbury Press*, 442–446.

Mitchell, T. (1997). Machine learning. *WCB McGraw-Hill*, 128–141.

Putnam, R. (1995). Tuning in, tuning out: The strange disappearance of social capital in America. *Political Science and Politics*, 664–683.

Singh, M. P. (2002). Trustworthy service composition: Challenges and research questions. *Proceedings of the Autonomous Agents and Multi-Agent Systems Workshop on Deception, Fraud and Trust in Agent Societies,* Heidelberg: Springer, 39–52.

Taurisson, N., & Tchounikine, P. (2004). Supporting a learner community with software agents. *Educational Technology & Society,* 7 (2), 82–91.

Tsai, W., & Ghoshal, S. (1998). Social capital and value creation: The role of intrafirm networks. *Academy of Management Journal*, 41(4), 464–476.

Upadrashta, Y., Vassileva, J., & Grassmann, W. (2005). Social networks in peer-to-peer systems. *Paper presented at the 38th Hawaii International Conference on System Sciences*, January 3-6, 2005, Hawaii.

Wachter, R. M., Gupta, J. N. D., & Quaddus, M. A. (2000). It takes a village: Virtual communities in supporting of education. *International Journal of Information Management*, 20(6), 473-489.

Wasko, M. M., & Faraj, S. (2005). Why should I share? Examining social capital and knowledge contribution in electronic networks of practice. *MIS Quarterly*, 29(1), 35–57.

Wellman, B. (1997). An Electronic Group is virtually a social network. In Sara Kiesler ed., *Culture of the Internet*, Hillsdale, NJ: Lawrence Erlbaum, 179-205.

Yang, S.J.H. (2006). Context Aware Ubiquitous Learning Environments for Peer-to-Peer Collaborative Learning. *Educational Technology & Society*, 2006. 9 (1), 188–201.

Yang, S.J.H., Chen, I., & Shao, N., (2004). Ontological enabled annotations and knowledge management for collaborative learning in a virtual learning community. *Educational Technology & Society*, *7* (4), 70–81

Yolum, P. & Singh, M. P. (2002). An agent-based approach for trustworthy service location. *Proceedings of 1st International Workshop on Agents and Peer-to-Peer Computing (AP2PC),* 45–56.

Zhang, G., Jin, Q., & Lin, M. (2005). A framework of social interaction support for ubiquitous learning. In *Proceeding of the 19th International Conference on Advanced Information Networking and Applications (AINA'05).*

Zhang, Y., & Tanniru, M. (2005). An agent-based approach to studying virtual learning communities. *Proceedings of the 38th Hawaii International Conference on System Sciences*.