BITING NEWCOMERS TO IMPROVE COLLABORATIVE LEARNING SYSTEM: AN OPPORTUNITY COST PERSPECTIVE

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Abstract

This paper introduces a computational model of online collaborative learning system and investigates how the heterogeneity of opportunity cost among users initiates a vicious cycle of accumulation of unnecessary duplicate postings and eventually the system shuts down. Further examination explores how deterring newcomers improves collaborative learning system efficiency by reducing unnecessary duplicate postings resulting from opportunistic behavior and explains why extrinsic rewards may fail to improve use of a collaborative learning system due to an unfavorable alignment between opportunity cost and cognitive structure of knowledge. This paper suggests a new approach for explaining the relationship between opportunity cost and collaborative learning system success as well as for identifying and aligning the opportunity cost of using the system, which is suggested as a critical factor to system success.

Keywords: Collaborative learning, knowledge management, opportunity cost, extrinsic rewards
1 INTRODUCTION

The abbreviation RTFM (loosely translated as Read the Flaming Manual) references popular Internet slang in online collaborative learning systems (CLS hereafter) that is meant to deter new participants from excessive duplicate posting of questions for already known problems. According to Wikipedia, this RTFM instruction is a response given when a community participant believes a question could be easily answered by reading the relevant user manual or instructions. Wikipedia itself, one of the largest good-willed open CLS suffers from harsh and sarcastic responses to newbie participation. One of Wikipedia’s guideline, “Please do not bite newcomers” discourages both “biting the newcomers” and “common newcomer errors” such as posting articles unworthy of the community’s standards.

These extreme tactics of deterring newbie questions sometimes interpreted as a psychological self-esteem seeking behavior, but it is also useful for filtering out the source of forum spam. Because by not searching first, unnecessary duplicate posts in a CLS increase the search cost and hamper the system. For example, longboard skateboarding community members are tired of repeatedly answering the same question about the differences between a longboard skateboard and a normal skateboard, and state “Being short on time and opening posts that are just repeats gets really annoying.”

User’s shirking in a CLS, like duplicate posting without searching first, can be explained by opportunity cost. A user can "learn" from knowledge repository by searching previous questions and answers, however the user can ask the question other users and save the search cost, if other users generously answers the user’s question. This kind of shirking behavior and annoyed responses from other users suggest that a CLS can have heterogenous opportunity cost distribution among its users. Some users simply have better things to do than search, while others are annoyed by excessive duplicate posting because they want efficient use of the system. Many knowledge management studies have suggested a relationship between opportunity cost and use of knowledge management systems (KMS hereafter), which usually includes functions for CLS, like online Q&A boards and mailing lists, to provide easier knowledge sharing (Haas and Hansen, 2005; Pinsonneault and Rivard, 1998). Therefore opportunistic shirking may lead to excessive duplicate posting, which congests the system with unnecessary duplicate posts.

Also, many scientists studying information overload addressed the importance of a filtering mechanism that could remove such unnecessary knowledge objects, to improve overall knowledge management performance (Alavi and Leider, 2001; Maier and Remus, 2003; Belkin and Croft, 1992; Manning and Schutze, 1999; Cohen and Singer, 1996; Chen, H. 1995; Haykin, S. 1999). Although many studies addressed the importance of filtering unnecessary knowledge, it appears no academic papers have examined the link between junk accumulation and opportunistic shirking. Accumulated junk within CLS due to opportunistic behavior increases the overall search cost, eventually users with relatively minor opportunity cost may participate in duplicate posting, thereby increasing junk even further. Consequently, the CLS may stop working effectively due to vicious cycle of duplicate posting.

Extrinsic rewards in knowledge sharing are also a puzzle to academic researchers. Constant et al. (1994, 1996) and Huber (2001) suggested that a lack of sufficient extrinsic and intrinsic rewards to compensate individuals for the costs of sharing knowledge inhibits knowledge sharing. However, Bock et al. (2005) empirically verified that extrinsic rewards do not always encourage KMS usage. In the opportunity cost viewpoint, heterogeneous opportunity cost distribution across users can affect the viability of extrinsic rewards. When a user is burdened by heavy opportunity cost however the user has a great potential to contribute to the system, presenting substantial extrinsic rewards can be

1 http://www.tldp.org/LDP/intro-linux/html/sect_01_02.html
2 http://en.wikipedia.org/wiki/Wikipedia:Please_do_not_bite_the_newcomers
3 http://en.wikipedia.org/wiki/RTFM
4 http://en.wikipedia.org/wiki/Internet_forum#Double_posting
important to improve CLS efficiency, since it can compensate opportunity cost of users with potential to contribute. If a user under heavy opportunity cost does not have proper knowledge potential, extrinsic reward may be wasted because the user cannot effectively contribute to the system.

I suggest a computational model to investigate the following research questions: 1) How does the heterogeneous individual opportunity cost of using CLS initiate a vicious cycle of excessive duplicate posting? 2) Can newcomer biting increase overall CLS efficiency? 3) How does individual opportunity cost distribution affect extrinsic rewards?

In section 2, the relevant literature is reviewed and research hypotheses are derived. Section 3 explains the models and analysis results. Section 4 suggests implications of this study and directions for future research.

2 LITERATURE REVIEW

2.1 Opportunity cost of CLS usage and accumulation of unnecessary duplicate postings

A computer-supported online CLS can be a vital subsystem of KMS, because a CLS usually provide functions which can help critical activities of a KMS, such as knowledge repository, efficient search and knowledge sharing, and collaborative environments (Eichler, 2003; Neumann and Schupp, 2003). Since Nonaka (2000), many researchers have warned that the opportunity cost of using KMS may hamper overall firm performance because significant time and resources must be used to search and transfer knowledge (Ba et al. 2001; Haas, 2005; Kankanahalli et al., 2005; Markus 2001; Teece, 2000).

At the organizational level, it is clear that each individual’s time and resources spent on using KMS may have been assigned to a better use, if such use is available. However, at the individual level, a few studies have investigated this issue only recently. Lack of consideration for the influence of individual characteristics on knowledge sharing may result in a KMS failure (Carter & Scarbrough, 2001; Voelpel, Dous, & Davenport, 2005). Various issues such as information systems (Wasko & Faraj, 2005), organizational behavior (Bordia, Irmer, & Abusah, 2006), and strategic management (Reagans & McEvily, 2003) were examined at the individual level of knowledge sharing. However, these previous studies implicitly assumed a KMS user, burdened by opportunity cost, would simply do not use the system at the first place. However, as a CLS provides functions for collaborative learning and knowledge sharing as a part of knowledge management (Eichler, 2003; Neumann and Schupp, 2003), a user with heavy opportunity cost has more option than giving up using the system entirely. The user can ask other users to solve the problem for him and simply do better things than searching the system, taking advantage of other users’ endowments for the CLS. Therefore, I propose the following research hypothesis:

H1: Without filtering mechanisms, strategic duplicate posting from users who are under heavy opportunity cost initiates positive feedback of increasing search cost and eventually even users under small opportunity cost join duplicate posting. As a result, the CLS may shut down completely.

2.2 Biting newcomers

To reduce duplicate posting, there are two different possible approaches. First, the traditional method is an ex-post solution, which cleans up and filters out accumulated duplicate postings. Nevertheless, this process is costly, due to monitoring and assessing the knowledge value by machine or human efforts. Many researchers suggested the importance of information filtering to avoid information overload. Among them, computer scientists focused on the more specific issue of machine based filtering (Belkin and Croft, 1992; Manning and Schutze, 1999; Cohen and Singer, 1996; Chen, H. 1995; Haykin, S. 1999). However, the subject of filtering from these studies is usually focused on the knowledge object, not on the human who produces unnecessary knowledge objects such as duplicate posting.
The highest level of knowledge is exchanged in communities. Many organizations may be particularly interested in these high-level users. However, many studies have suggested, many organizations may impose a low initial knowledge cost, however, the opposite situation may exist. If experienced workers have other pressing priorities while inexperienced workers are eager to learn from the CLS as a subsystem of KMS, the correlation between opportunity cost and experience level may be reversed. Haas and Hansen (2005) also speculated that KMS usage might be more costly to experienced individuals because of the opportunity costs in performing other value-added tasks. Therefore, two kinds of possible alignments between opportunity costs and individual knowledge level exist and both should be considered.

To avoid confusion, I define the term opportunity valuation as the reverse of opportunity cost. A CLS user has high opportunity valuation of the system if the user has a low opportunity cost, while a user with a high opportunity cost has a low opportunity valuation. For the first case, an individual opportunity valuation helps us to understand the system. Thus, the CLS is valued more by users who have relatively more initial knowledge, while it is less valued by users with lesser knowledge. A typical example would be an expert in a specific knowledge community such as Linuxquestions.org or MSDN. The higher level of knowledge is exchanged in such communities, and if one aims to learn high-level knowledge, there are practically no other places to go. However, for inexperienced newcomers it may not be easy-to-use because of a considerable amount of FAQs and manuals, even for the forum use itself. If newcomers are assumed to have such low levels of initial knowledge and likely to ask well-known questions, then targeting these users may reduce the duplicate post without much loss of contribution potentials. Therefore, I suggest the following hypothesis:

\[ H2a: \text{When individual opportunity valuation positively correlates with initial knowledge level, deterring users with low initial knowledge level may increase overall learning effectiveness of CLS.} \]

The opposite case occurs when individual opportunity valuation of CLS usage negatively correlates with initial individual knowledge level. A good example would be an open and general Q&A system, like Yahoo Answers and Ask.com. For users with a low initial knowledge level it is easy to use, thus imposing a low opportunity cost because there are no rules prohibiting duplicate posts whatsoever. However, for users with a high initial knowledge level, such general Q&A boards may not be so attractive because more suitable and specific knowledge communities are available, and those general Q&A systems produce simple and unchallenging questions. In this case, deterring users with low initial knowledge level may not be so productive, because it targets users with less potential to contribute and less likely to duplicate post, while users with more potential to contribute and more likely to duplicate post are not affected. Therefore, in this situation deterring low initial knowledge level users removes the only users who actually want to contribute and users with heavy opportunity cost and with high potential to contribute remain unaffected. I suggest the following hypothesis:

\[ H2b: \text{When individual opportunity valuation negatively correlates with initial knowledge, deterring users with low initial knowledge level may decrease overall learning effectiveness of CLS.} \]

### 2.3 Extrinsic reward puzzle and opportunity cost

Studies on the relationship between extrinsic rewards and successful knowledge management are ambiguous so far. As Davenport (2002) suggested, many organizations impose various extrinsic rewards such as an annual conference at a resort and mileage programs (Hyoun and Moon 2002).
Bartol and Locke (2000) identified several important aspects of organizational reward systems that are useful for motivating individuals to perform targeted behaviors. However, empirical results are mixed in examining the effects of extrinsic rewards.

Extrinsic rewards such as bonuses, promotions, and higher salaries had positive effects on the frequency of knowledge contribution (Kankanahalli et al., 2005; Cabrera et al., 2006; Kulkarni et al., 2006; Kim and Lee, 2006; Constant et al. 1994, 1996; Huber 2001). However, extrinsic rewards did not always show positive effects on knowledge sharing. Deci et al. (1999) found that extrinsic rewards negatively affected free choice and resulted in no effect on individual incentives. Bock and Kim (2002) indicated that extrinsic rewards might negatively affect knowledge sharing attitudes. Bartol and Srivastava (2002) argued that if database tracking and monitoring of knowledge sharing exists, extrinsic rewards might have a positive effect on knowledge sharing. Arthur and Aiman-Smith (2001) showed that a gain sharing plan increased employees’ suggestions at the early stage; however, it soon leveled off and started to decline over time.

As Wang and Noe (2010) suggested, investigating this extrinsic rewards puzzle with a relatively new approach can be a valuable addition to the knowledge management field. In the opportunity cost perspective, extrinsic rewards can compensate opportunity cost. In the transaction cost view, the individual will act only if the institutional setting compensates the self-interest lost by the action, such as sharing knowledge (Osterloh & Frey, 2000). In this context, the effectiveness of extrinsic rewards differs according to how the opportunity cost is distributed among CLS users. If opportunity valuation is positively correlated with initial knowledge level, extrinsic rewards may not be effective because users with a high valuation of the system are rewarded, while users with low valuation of the system struggle to get rewards because they have less potential to contribute. On the other hand, if opportunity valuation is negatively correlated with initial knowledge level, then extrinsic rewards may be effective because they can compensate high opportunity cost users who have a high potential to contribute. Thus, in the negatively correlated case, the extrinsic reward can be a win-win strategy since low initial knowledge level users have a high valuation of the system and high initial knowledge users are compensated for their high opportunity cost.

Therefore, I suggest the following hypothesis:

\( H3a: \) When individual opportunity valuation positively correlates with initial knowledge level, extrinsic rewards are less effective in increasing overall learning than negatively correlated cases.

\( H3b: \) When individual opportunity valuation negatively correlates with initial knowledge level, extrinsic rewards are more effective at increasing overall learning than positive correlated cases.

## 3 MODEL AND ANALYSIS

Suppose a knowledge network consists of total \( k \) knowledge objects. Each knowledge object has its own level. A high-level knowledge object depends on prerequisite knowledge objects in order to understand it. A prerequisite knowledge object exists in one level below each higher level knowledge object, except for the lowest knowledge level. A CLS has three basic functions: 1) A user can ask a question about a specific knowledge object. 2) A user can answer a question. 3) A user can search for previous posted questions and answers. The CLS has total \( N \) users. All users are required to use the system for an indefinite period. Each user accesses the system in a random sequence and has a unique initial knowledge level, \( k \), which is uniformly distributed over \([0, k_{\text{MAX}}]\). Each user has a different opportunity valuation \( v \) of the system, which is uniformly distributed over \([0, v_{\text{MAX}}]\). Note that \( v_{\text{MAX}} \) is an open-ended parameter. Users’ opportunity valuation can be positively correlated with users’ initial knowledge level, \( v/v_{\text{MAX}} = k/k_{\text{MAX}} \), or can be negatively correlated, \( v/v_{\text{MAX}} = (1-k)/k_{\text{MAX}} \), according to each case the model aim to simulate, where \( v_i \) and \( k_i \) denotes user \( i \)'s opportunity valuation and initial knowledge level, respectively.

According to each user’s opportunity valuation \( v \), three parameters are assigned to the user: 1) Initial amount of credit \( c \), \( c=v \) required to search the system and answer questions. The higher the user’s opportunity valuation, the more initial credit the user has. If the credit goes below the minimum
required amount to perform search/answer, the user gives up using the system. The initial credit can be interpreted as the initial endowment for the CLS and it is assumed to be positively correlated to opportunity valuation. 2) Number of searches \( s, v \) performed to obtain the right answer per each use of the system. The higher the user’s opportunity valuation, the more searches the user performs per system use. 3) Number of credits \( w, v = v_{\text{MAX}} - v \) required to answer a user question. The higher the user’s opportunity valuation, the less credit is required to answer other users’ questions. The initial amount of credit \( c \) represents how much a user values the system initially. The search conversion ratio \( s \) and the answering conversion ratio \( w \) represent efficient and eager use of the system.

A user’s behavior is defined as the following: All users aim to know all the knowledge objects. The user selects an unknown knowledge object, which can be only one level higher than the known knowledge object. In other words, without knowing the prerequisite knowledge object, a user cannot target a higher-level knowledge object. If the user has positive credits, the user performs a search for \( s \) times for the designated knowledge object. If the search produces an answer to the question among the duplicated postings, the user acquires the knowledge object and increases in user credit by one. The probability of finding a suitable answer is given as: \( p_i = n_{a,i}/n_i \) where \( n_{a,i} \) is the number of well-answered postings for knowledge object \( i \), and \( n_i \) is the number of total postings for knowledge object \( i \). Also, the respondent of the selected answer receives an extrinsic reward, if available. If the search fails after \( s \) number of search attempts, the user’s credit decreases by one and the user posts a question about the target knowledge object, which may increase the number of duplicated postings. The user can check whether his or her questions were answered in the next period without another search attempt. Finally, a user finds an unanswered open question and tries to answer it but only if the answer for the question is known to the user and the user has sufficient credit beyond the required amount to answer a question \( (c > w) \). By answering a question, the user’s credit decreases by \( w \). The question is properly answered only by consuming the respondent’s time and resources, which is represented by credit in the model. Otherwise, the question is considered unanswered or badly answered indicated by a statement such as “bump,” “I don’t know that either.” Figure 1 shows a pseudo code of how a user performs search, posting, and answering by using the CLS for each period.

<table>
<thead>
<tr>
<th>A user accesses the system</th>
</tr>
</thead>
<tbody>
<tr>
<td>If first time, select a random target knowledge object</td>
</tr>
<tr>
<td>Check if the user's posting is answered by someone else</td>
</tr>
<tr>
<td>If answered,</td>
</tr>
<tr>
<td>( c = c + 1 )</td>
</tr>
<tr>
<td>Answerer gets extrinsic reward</td>
</tr>
<tr>
<td>Select a new target knowledge object</td>
</tr>
<tr>
<td>Else,</td>
</tr>
<tr>
<td>Maintain previous target knowledge object</td>
</tr>
<tr>
<td>If ( c &gt; 0 ), the user search the system, ( s ) times, for the target knowledge</td>
</tr>
<tr>
<td>If search successful,</td>
</tr>
<tr>
<td>( c = c + 1 )</td>
</tr>
<tr>
<td>Answerer gets extrinsic reward</td>
</tr>
<tr>
<td>Select a new target knowledge object</td>
</tr>
<tr>
<td>Else,</td>
</tr>
<tr>
<td>( c = c - 1 )</td>
</tr>
<tr>
<td>Posts the question regardless of duplicate posting</td>
</tr>
<tr>
<td>If ( c &gt; w ), the user tries to answer a question</td>
</tr>
<tr>
<td>By answering a question, ( c = c - w )</td>
</tr>
<tr>
<td>The user logs out</td>
</tr>
<tr>
<td>Next user accesses the system</td>
</tr>
</tbody>
</table>

**Figure 1. Pseudo code of CLS user rules**

It is assumed that the user does not know the quality of the answer before opening a post although in the real world a user may guess the quality of the content by considering the number of replies, votes, or title. Although in the real world such information is provided by either the system or other users, I suggest that above assumptions still reflects the difficulty in finding a good answer among duplicated postings since the mechanisms to reduce search cost do not allow a user to perfectly know the quality of the answer before opening the post. Basic model parameters are shown in the table below:
### Table 1. Basic model parameters.

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of agents (N)</td>
<td>100</td>
</tr>
<tr>
<td>Number of total knowledge objects</td>
<td>99</td>
</tr>
<tr>
<td>Number of levels in knowledge network</td>
<td>3</td>
</tr>
<tr>
<td>Number of knowledge objects per each level</td>
<td>33</td>
</tr>
<tr>
<td>Stop condition</td>
<td>Difference of total knowledge learning</td>
</tr>
<tr>
<td></td>
<td>between current and previous step less than</td>
</tr>
<tr>
<td></td>
<td>0.00001</td>
</tr>
<tr>
<td>Number simulations for each experiment</td>
<td>100</td>
</tr>
</tbody>
</table>

Two different relationships between opportunity valuation and initial knowledge level are investigated: positive correlation and negative correlation.

#### 3.1 Effect of positive feedback on duplicate posting

Hypothesis 1 derives from an expectation that even if users with only a low opportunity valuation of the system start accumulating duplicate posts, the overall search cost increases, thus gradually leading more users to duplicate post and an eventual system shut down. Both positively and negatively correlated cases are experimented with using different values of $v_{\text{MAX}}$.

To measure the whole system’s knowledge learning, global knowledge learning is defined as:

$$G = \sum_{j=1}^{N} o_j / \sum_{j=1}^{N} k_{\text{MAX}}$$

Where $o_j$ is the number of knowledge objects known to the user $j$.

The experiment showed that a search fail increases as time passes and junk accumulates as more users abandon trying to search first.

For positively correlated cases, sample results are shown below:

![Global knowledge acquisition and failed search history, positive correlation, $v_{\text{MAX}} = 10$](image)

In the examples shown in Figure 2, global knowledge acquisition increased initially, however as more users performed failed searches, they joined duplicate posting without searching first. The learning stopped at 0.594 and did not increase further. Although at a given $v_{\text{MAX}}$ the simulation ran 100 times, each simulation has a slightly different shutdown timing. Therefore, the aggregated value for each step cannot be derived. However, all simulations showed a similar pattern of shutdown as well as search attempts and fails.

Increasing the parameter $v_{\text{MAX}}$ will increase the maximum knowledge level. The average final knowledge acquisition for 100 attempts for a given $v_{\text{MAX}}$ value is shown below.
As $v_{\text{MAX}}$ increases, final global knowledge acquisition also rapidly increases. When the system is highly valued by intended users, it works efficiently and increases global knowledge acquisition to a higher level. In the following analysis, for positively correlated case, $v_{\text{MAX}}=10$ is chosen as a benchmark parameter, since too low or too high value of $v_{\text{MAX}}$ the system reacts in a very small scale or very large scale, making it relatively hard to observe and compare results. Although the overall system behavior remains same, the benchmark parameter $v_{\text{MAX}}=10$ shows the best human readable analysis results.

Figure 4 shows that for negatively correlated cases, the results indicates significantly lower CLS efficiency. The shutdown pattern is very similar to positively correlated cases and is distinct for reaching its maximum global learning slightly faster, although the reached maximum is significantly lower than the positive case. Total search attempts decrease quicker, and there are more frequent and early failed searches.

Also, increasing $v_{\text{MAX}}$ showed much less effectiveness than the positively correlated case, in Figure 5.
Because of negative correlation, users with a high level of initial knowledge and a low opportunity valuation do not benefit. This suggests no matter how much valuation low level users have, if users who have the ability to contribute do not value the system, the system may not work. For negatively correlated case, setting the same value of $v_{\text{MAX}}$ as the positive case ($v_{\text{MAX}} = 10$) makes the system reacts in a too little scale and hard to compare results, therefore the value $v_{\text{MAX}}=20$ is used as a benchmark parameter. Results suggest that even when a small number of users start duplicate posting, it gradually increases the overall search cost and more users begin to duplicate post. If posting without searching is allowed, users with a high opportunity cost damage the system and may even initiate positive feedback of a system crash. As mentioned earlier, many researchers suggested filtering out and cleaning up unnecessary knowledge objects within the system to maintain the system’s viability. In addition to addressing the importance of a filtering mechanism, I further suggest that if high opportunity cost users are allowed to strategically duplicate post, the system may eventually fail without properly managing opportunistic behaviors.

3.2 Deterring newcomers

Biting newcomers may be a viable strategy because if they are presumed to be so ignorant that they could not understand the basic manual, then they may have to be removed as a source of duplicate posting that hampers overall search efficiency. In reality, some newcomers with a high initial knowledge level may duplicate post because such users are not fully familiar with sophisticated search functions. In this experiment such false negatives are not considered, to focus on strategic behaviors of CLS users. Hence, the strategy is interpreted as deterring low initial knowledge level users.

The deterrence level parameter ranges from 0 (required initial known knowledge objects) to maximum available knowledge objects, $k$, normalized to $[0,1]$. For positively correlated cases, the averaged maximum global learning for 100 simulation runs along with deterrence level is shown below:

![Figure 6. Average global knowledge learning along deterring level, positive correlation, $v_{\text{MAX}} = 10$](image)

The result shows at certain level of deterring, the system dramatically outperforms than that of no deterring. For positive correlated case, the target of deterring is well aligned with CLS objective that is effectively increasing global knowledge learning, because deterring removes users with low potential of contribution and high potential of duplicate posting. However, as deterring level increases, too many users are blocked and damage the system utilization. Also, a well-set deterring level shows dramatic increase of global knowledge learning, which explains why many expert knowledge communities often heavily deter newcomers, especially if $v_{\text{MAX}}$ is not very high. Only under high $v_{\text{MAX}}$ value, deterring newcomers did not get much increase because many users have enough patience to deal with duplicate posts. Therefore, I suggest that hypothesis H2a is supported.

For negatively correlated cases, the result is shown below.
As expected, in negatively correlated cases, deterring newbies did not solve any problems because it only removed users who wanted to contribute, even if they had no ability to do so. Therefore, hypothesis H2b is supported. This analysis helps to explain why topical and expert-based knowledge communities deter newcomers while general and easy-to-use knowledge communities do not. If the CLS is the only place to acquire high-level expert knowledge, it may be viable to deter newcomers, thus targeting the right source of garbage creation. On the other hand, if the system is designed to serve general and common knowledge-seekers and does not attract experts, there is no need to restrict access. These findings are consistent with real world phenomena in which specific and expert systems often deter newcomers while general Q&A systems do not.

### 3.3 Extrinsic rewards

In this set of experiments, setting extrinsic rewards are an alternative to newcomer deterrence. The amount of extrinsic rewards ranges from 0 to $v_{\text{MAX}}$. Setting the amount of extrinsic reward at $v_{\text{MAX}}$ means that even for a user with the highest opportunity cost, a single selected answer can fully compensate the user’s opportunity cost incurred by answering a question.

For positively correlated cases, the result is shown below with normalized extrinsic rewards.

As the amount of extrinsic reward increases, global knowledge acquisition slowly increases. However, it outperforms a deterrence strategy only with very high level of extrinsic reward, which may require significant managing costs. For positively correlated cases, deterring newcomers can be a relatively quicker and easier solution than imposing extrinsic rewards.

For negatively correlated cases, the hypothesis was built on the expectation that by rewarding users with a high potential to contribute and a high potential to duplicate post, the system may increase its effectiveness. However, the result showed no significant performance improvement.
The system’s response to extrinsic rewards showed more of a random movement and much less effectiveness than positively correlated cases. The reason behind the result is the cognitive hierarchy of the knowledge network. The following figures show the average levels of question and answer changes as the simulation ran.

**Figure 9.** Average global knowledge acquisition along normalized extrinsic reward, positive correlation, $v_{\text{MAX}} = 20$

For positively correlated cases, average-level of questions start at about the middle and fall quickly at the early stage. This means that high-level problems are solved quickly because users with a high initial knowledge level have both high opportunity valuation and extrinsic reward. After solving high-level problems first, users focus on solving low-level questions that are suffering from duplicate posting. However, for negatively correlated cases, high-level questions accumulate while low-level questions are slowly answered. The following figures further investigate the problem.

**Figure 10.** Average level of question and answers, left for positive correlation, $v_{\text{MAX}} = 10$, right for negative correlation, $v_{\text{MAX}} = 20$. Extrinsic rewards are set to maximum.

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In Figure 11, the average reward per answer is illustrated according to the users’ initial knowledge level. Users designated as high are those who have more initial knowledge than average, while low characterizes users who have less than average knowledge. For positive cases, rewards assigned to high initial knowledge level users with more opportunity valuation of the system surpass low initial knowledge level users. Because of high-level users’ contribution potential and higher valuation, extrinsic rewards mainly go to high-level users. Low-level users do not have both enough valuation and ability to contribute, thus receiving relatively smaller rewards. On the other hand, for negative cases, early stage low-level users get slightly more rewards per answer. This means even if high initial knowledge level users with a high opportunity cost contribute, they do not enjoy the rewards enough to compensate for the opportunity cost because in the early stage, the questions are usually in the low level thus presenting a high competition for reward given the eagerness of low level users to participate.
Figure 11. Average rewarded answers, left for positive correlation, $v_{\text{MAX}} = 10$, right for negative correlation, $v_{\text{MAX}} = 20$. Extrinsic rewards are set to maximum.

Only after the system runs for some steps and global knowledge increases, high-level users achieve relatively more rewards than low-level users because the ability of low-level users to contribute diminishes. We argue that the analysis results in this case is quite important, because it suggest that the relationship between cognitive knowledge structure and opportunity valuation may prevent the last resort of encouraging the use of CLS, extrinsic reward, and can be a major factor which decides the success and failure of policy of extrinsic reward, as previous research showed mixed results. Hypothesis H3a and H3b are not supported, however the analysis suggested that cognitive structure may play an important role in utilizing extrinsic rewards.

4 CONCLUSION

This paper suggests a computational model linking CLS effectiveness and opportunity cost. The experiments showed how vicious cycle of accumulation of duplicate posting may eventually shutdown the system. Two different strategies to solve the opportunity cost problem were introduced and tested. A real world solution that deters newbie users who are assumed to have low contribution potential is tested both when opportunity valuation is positively correlated with a user’s initial knowledge level and when those are negatively correlated. For positive correlation, deterring low-level users showed a significant improvement of system efficacy, while for negative cases the strategy only damaged the system. Imposing extrinsic rewards as opportunity cost compensation is also tested. For positive correlation, extrinsic rewards showed a positive reaction to the system. However, it may still be costly and less efficient relative to the deterrence strategy. For negative correlation, the cognitive structure of the knowledge network lessens the efficiency of extrinsic rewards since, at least at the early stage when only relatively low-level knowledge is exchanged.

The model captured vital functions of CLS like vicarious learning, searching, storing and retrieving, however it does not fully reflect all the major functionalities of KMS introduced by previous studies (Huber, 1999, 2001). The characteristics of search functions provided by a CLS can also be an extendable parameter. In reality, a user’s intended search target and search keywords do not always match, and sometimes search function can produce unintended results which may be both beneficial or nuisance. This kind of uncertainty in search function can be an interesting parameter which may suggest balance between exploration and exploitation in searching for knowledge.

References


