Knowledge sharing in Peer-to-Peer Online Communities: The Effects of Recommendation Agents and Community Characteristics

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Abstract

Knowledge sharing (KS) is generally performed in a centralized fashion, through a knowledge repository. However, the centralized knowledge management systems may sometimes cause problems in sharing knowledge. One potential solution is to conduct KS in a decentralized network supported by peer-to-peer technology. While extensive research has been done to address the flaws of current reputation-based feedback mechanisms for promoting knowledge diffusion in peer-to-peer communities, some serious drawbacks of feedback mechanisms, namely dimensionality and interaction-dependency effects, have been overlooked. Using an agent-based simulation, this paper examines these effects while also considering characteristics of the community. Results of our simulation show interesting findings, for example, that negligence of knowledge dimensionality and interaction-dependency in designing reputation mechanisms has a major negative effect on community knowledge performance. Further, more complex knowledge adversely affects community-level diffusion outcomes whereas greater network density improves them.

1. Introduction

Knowledge sharing (KS) has been a core focus of the recent knowledge management (KM) literature [4]. While this process has generally been centralized through knowledge repository systems, the inefficiency of such systems is being increasingly recognized. Knowledge repositories have been shown to be slow in generating content and prone to errors [8]. To mitigate drawbacks of centralized KS systems, peer-to-peer KS has been promoted. In such decentralized KS mechanisms, interpersonal networks of knowledge workers are shaped and each individual adopts roles of both knowledge producer and knowledge user. Such communities have been shown to be more effective than central repositories [18].

KS in communities also faces barriers. Individuals in such communities should heavily rely on interpersonal trust [23] to acquire or share the knowledge. Thus, trust building is one of the most challenging tasks that have to be done. As a result of such importance, a vast number of articles in the domain of peer-to-peer KS have been devoted to designing and implementing mechanisms through which signals of trust can be transmitted to members [21]. In general, such efforts have focused on generating reputation for members as the signal of trust. The core idea is that evaluation by a focal member can be an effective proxy to approximate trustworthiness of that member. However, some studies have pointed out flaws associated with the existing reputation mechanisms [5]. The core argument in these articles is that since evaluations of reputation are done by members of the community, they can be affected by cognitive biases. The problem magnifies when the community is virtual and members can use dummy profiles to rate themselves or trade positive evaluations.

While attention has been given to tackling cognitive biases, their effects, and potential remedies, other aspects of current reputation mechanisms have been overlooked. In fact, evaluation of reputation in a peer-to-peer community is highly dependent on specific interactions among members and as a result, the visible span of a focal member’s knowledge is highly bounded by the knowledge that (s)he explicated and experiences. Such evaluations can be biased towards those aspects of knowledge which have been already exploited. Further, the knowledge set of individuals can have multiple dimensions. Most of the current reputation systems report a single value over the whole range of an individual’s knowledge set. Such mechanisms may be flawed as some individuals might be trustworthy in certain aspects and as a result of only those aspects, be exploited. This implies that if the signal is not clear on which dimension of knowledge a member is trustworthy, (s)he might be approached for
a dimension of knowledge which is not an area of strength. This can lead to false beliefs spreading within the community.

The above phenomena stem from ignoring interaction-dependency of current reputation mechanisms (interaction dependency implies that members can rate each other’s knowledge only if they interact with each other) and negligence of knowledge dimensionality (which refers to the fact that individual’s knowledge includes multiple elements) in calculating and signaling reputation values of community members. Seeking to address these issues, this study sheds light on how interaction-dependency of trust promotion mechanisms and negligence of knowledge dimensionality can endanger knowledge diffusion in a community, and suggests some approaches to mitigate such effects.

2. Research Background

Turbulent environments require organizations to develop rapid response mechanisms. One strategy used to attain this goal is exploiting current organizational knowledge and combining it with prior knowledge to respond to emerging needs. As a result, KS is considered to be one of the most important steps in organizations [2]. To efficiently exploit their embedded knowledge, organizations need to encourage their employees to share their knowledge in exchange for acquiring colleagues’ knowledge. However, this process is not always straightforward.

Traditionally, organizations have tried building centralized KS systems in which their members stack their knowledge in a repository and access it as needed [9]. It has been found that a decentralized peer-to-peer community can remedy problems of centralized KS networks, such as lack of ability to share tacit knowledge [14]. In a peer-to-peer community each user can be directly connected to another user.

Weblogs, wikis and discussion forums have been recognized as decentralized technologies which enable KS networks [22]. Among these, discussion forums are the most popular [3], as they enable users to easily connect, interact and rate each other. The discussion forum (also called a discussion board or bulletin board) is one of the earliest technologies for collaborative knowledge creation and KS. Such discussion forums have been traditionally used among communities of practice to facilitate KS [10]. We base our modeling of the current situation on currently used forum discussion technologies such as vBulletin.

Opposing views on the same aspects of knowledge might coexist in decentralized KS communities. The evaluation of existing knowledge can therefore be a challenge for knowledge seekers in the network. It has been argued that individuals use trustworthiness of peers as a proxy to evaluate their knowledge. Extensive research has addressed the issue of trust building in peer-to-peer communities [19]. Communities use reputation mechanisms to signal trust of community members. In the context of peer-to-peer communities, an individual’s trustworthiness is defined by a peer as his or her ability to provide services to other peers [23].

Reputation is defined as “what is generally said or believed about a person’s or thing’s character or standing” [11]. In the context of peer-to-peer communities, reputation is mostly the evaluation of a focal peer by other peers. Reputation can be considered as a collective measure of trustworthiness (in the sense of reliability) based on the referrals or ratings from members in a community. Reputation as a trust signal preserves value associated with all interactions of an individual and is visible for other peers such that they rely on the collective measure of trustworthiness in absence of direct interaction.

With advancements in reputation mechanisms in product-focused communities, KS technologies began to realize the importance of signaling the quality of a member’s knowledge [6]. As a practical method, technologies such as vBulletin started providing the capability to rate each piece of knowledge shared by peers and then aggregate it to generate a reputation score for each member. As it has been shown, [23] reputation should be attributed to certain part of a member’s knowledge. Knowledge has been conceptualized as a multidimensional construct consisting of smaller bricks of knowledge and information [17]. That means that an individual can be trustworthy in a specific aspect of knowledge while (s)he can be a novice in other areas. However, the current way of integrating knowledge quality feedback in technologies such as vBulletin does not enable other peers to evaluate the knowledge source in the specific area of knowledge acquisition. One possible reason is that dimensions of knowledge in a community may be hard to identify. It may also be costly to explore and find orthogonal dimension of community knowledge.

3. Research Gap and Propositions

Research on reputation of peers has moved toward multi-criteria processes for evaluation. Results of studies suggest that reputation of a peer should be calculated based on a number of transactions, other users’ evaluations, the credibility of the rating users and the context of shared knowledge [23]. Then, they suggest that overall reputation should be the sum of those scores with proper weights assigned to each criterion. Further, there has been the suggestion to assign more weight to more recent interactions [21].
While these suggestions can remedy problems of single criterion evaluation mechanisms, they are still vulnerable in other aspects. The most important problem stems from the aggregation of different criteria. Such aggregations generate a single evaluation signal at the expense of eliminating some informative dimension of each criterion in evaluation. As mentioned in the previous section, knowledge itself is a multidimensional construct and rating it in an aggregative manner reduces the ability to find out in which dimension of knowledge a peer is more knowledgeable. Imagine a hypothetical situation in which knowledge of an individual has five distinguishable areas, which we will call knowledge dimensions. If that individual is knowledgeable in four areas and is a novice in the remaining area, then let us assume that (s)he has an overall reputation of 4/5. Let us hypothetically imagine that 4/5 is a relatively high reputation in the community and such reputation increases chances of him/her being contacted by other peers seeking knowledge. In this situation, there is a 20% chance of this individual being contacted to discuss an area of knowledge in which (s)he is a novice. Now, imagine another situation in which other peers are aware of the reputation of the focal peer in each dimension or area of knowledge. The focal peer is still approachable in the areas in which (s)he is an expert, but there is a lower likelihood of the individual being contacted to discuss the dimension of knowledge outside his/her areas of expertise. We refer to this issue as the knowledge dimensionality problem. As a result of knowledge dimensionality, aggregation of different dimensions of a peer’s credibility and trustworthiness can be more problematic. We are not aware of a prior study that has addressed this problem.

Some studies have addressed the issues and problems of peer evaluations [11]. One of the most important issues is the bias of users to positively rate other peers. Other issues are unfair ratings and change of identity [7]. Josang and his colleagues [11] noted these problems to be subjectivity problems of peer ratings. While approaching these problems can enhance the validity of current reputation mechanisms, issues of interaction-dependency in such evaluations remain unsolved. To further illustrate what we mean by the interaction-dependency fallacy of current reputation mechanisms, let us return to our earlier example in this section. Imagine the individual who is an expert in four areas out of five areas of knowledge. If other peers have a history of interaction with this individual over all five areas of knowledge for the same amount of time, and no judgment bias exists, then it can be predicted that reputation of that focal individual is correctly rated as 4/5. However, if that user has been contacted in his novice area of knowledge more than other areas and other peers are completely honest in their rating, then his/her reputation would fall below 4/5 and (s)he would not be approached as much as he can contribute knowledge to the community. Such fallacy in rating directly stems from interaction-dependency, which means that credibility of a peer cannot be correctly determined unless all areas of his/her knowledge are similarly exploited by the community.

While cognitive biases and single criterion evaluations are important problems of current reputation mechanism, and researches should be directed to remedy those problems, we argue that the dimensionality of knowledge and interaction-dependency of current reputation systems should be taken into consideration as well.

One might argue that problems of dimensionality and interaction-dependency do not have much effect on performance of communities. Such argument can be discussed if researchers can show how much difference in community performance emerges as a result of ignoring interaction-dependency or knowledge dimensionality. In order to study such an effect, one should be able to (a) measure knowledge diffusion performance of a community and (b) study the effect of dimensionality and interaction-dependency. This paper, by leveraging an agent-based modeling method, tries to simulate a peer-to-peer community and illustrate the effect magnitude of neglecting knowledge dimensionality and interaction dependency in designing knowledge promotion mechanisms. Illustrating the effect magnitude can be beneficial in realizing whether it is worth tackling the above problems while designing reputation mechanisms or if those problems do not practically or significantly make a difference in the knowledge performance of a community.

This paper tries to use the simplicity of modeling tools to design a situation in which cognitive biases do not exist and there is a single observable criterion on which credibility of a user can be known. If these two conditions are satisfied and if we suppose that those conditions remedy all fallacies of current peer-to-peer reputation mechanisms, then the outcome of modeling current reputation mechanisms which are based on peer evaluations should generate optimal performance. We also will model two different mechanisms which we suggest will remedy dimensionality and interaction-dependency. We intend to show that even in the absence of cognitive biases and in the presence of a suitable single observable criterion for evaluation, knowledge performance will be improved if our suggested mechanisms are utilized.
3.1. Reputation Mechanisms

We intend to model current reputation mechanisms in discussion forums (as the most popular peer-to-peer knowledge communities) which are mostly based on number of transactions and also based on aggregation of mutual evaluations [7]. According to Josang and his colleagues [11], among other important factors is context of each evaluation and credibility of raters. We assume that all contexts are equally important and raters are honest and credible in a way that they will not show any cognitive bias. We also assume that the only factor on which the user can be known to be knowledgeable is his/her value of knowledge, which is fully observable in an interaction and all users are capable of providing flawless feedback based on interaction. Thus one of the baseline mechanisms, which we call “subjective aggregation,” is a mechanism in which:

1. Knowledge has a specific number of dimensions, which is the same for all members of the community.
2. Knowledge dimensions can have a value of 1, -1 and 0, meaning that a member has a correct belief, a false belief or no knowledge in that dimension respectively.
3. Knowledge of community, which is a performance index of community learning, is the sum of all knowledge values of knowledge dimensions for all agents.
4. Reputation value of all members is visible for every other member in the community.
5. Members acquire knowledge from their neighbor with the highest reputation.
6. Value of each member’s knowledge dimension becomes observable in an interaction and other peers can correctly realize such a value.
7. Each member provides an honest feedback of value of knowledge dimension acquired from peer and the sum of those assigned feedbacks for each peer is signaled as reputation of the focal member.

This mechanism works based on aggregation of peer evaluations without cognitive bias and need to gather multiple criteria. We call this “subjective” based on Josang and his colleagues work [11], who contend that such evaluations are sourced from subjective interactions. To be able to control for internal validity of our model, we also assume a mechanism, called “transaction-based aggregation,” in which reputation is calculated by the number of interactions through which a member shares his/her knowledge with peers. In this mechanism:

1. To 5-are same as for subjective aggregation above.
2. Count of interaction through which a member has shared knowledge is an indicator of his/her reputation.

We include this mechanism as we believe this mechanism should naturally underperform the subjective aggregation mechanism as the latter calculated reputation does not signal the value of knowledge each member has. Then, we can check our model validity by testing for significant underperformance of transaction-based mechanism comparing to subjective aggregation mechanism.

In order to address interaction-dependency of reputation signals as well as the issue of knowledge dimensionality, we model two reputation mechanisms in which those issues are approached and solved. To overcome interaction-dependency, it should be noted that dependency fallacy is mainly due to reliance on subjective evaluations. As subjective evaluations are dependent on members’ interactions, such evaluations can be biased towards information dimensions through which the member has acquired knowledge. It can be assumed that an objective evaluation might not be prone to such fallacy. Further, dimensionality of knowledge can mislead members in case of aggregate evaluation ratings. That is, by aggregating ratings of different dimensions of knowledge, valuable information regarding each dimension of knowledge is lost, leading to sub-optimal knowledge diffusion within the community.

To remedy the problem of dimensionality, we assume that instead of aggregating evaluations, evaluation of each dimension of knowledge is available for users. In this way, we can assure that aggregation of different dimensions’ evaluation does not happen and thus richer information regarding members’ knowledge value is signaled and circulated in the community. So, the specific details of this “dimensional aggregation” mechanism are as follows:

1. To 4-are same as for subjective aggregation above.
2. Members acquire knowledge from their neighbor with the highest reputation in the dimension of knowledge in which they want to acquire knowledge.
3. Value of each member’s knowledge dimension becomes observable in an interaction and other peers can correctly realize such a value.
4. Each member provides an honest feedback of value of dimension of knowledge which is acquired from peer and sum of all feedbacks for each dimension is available as reputation signal.

This mechanism is not vulnerable to dimensionality of knowledge, thus we expect an increase in knowledge performance of community, comparing to subjective aggregation mechanism. Having a mechanism which does not reduce information on different dimensions of knowledge helps us to compare knowledge performance under conditions of aggregation and disaggregation of knowledge dimension values. Outcomes of such comparisons help us realize the effect of ignoring knowledge dimensionality in designing reputation mechanisms for knowledge communities.
Another issue with currently applied reputation mechanisms which rely on a peer’s evaluation is their interaction-dependency. We assume if objective aggregation of a member’s knowledge is available through standardized tests in the scope of community knowledge and that aggregated value is available as a reputation signal, then the effect of interaction-dependency is remedied. In fact, interaction-dependency fallacy emerges as a result of peer evaluations being dependent on subjective ratings which are based on unbalanced interactions. If peer ratings are based on objective evaluations of knowledge, then interaction-dependency is not a problem. We model this “objective aggregation” mechanism as follows:

1 to 5—are same as for subjective aggregation above
6-value of each member’s knowledge dimension is objectively calculated and sum of dimensions’ objective (i.e. actual) value is signaled as reputation.

We expect that, with overcoming interaction-dependency, this mechanism outperforms subjective aggregation mechanism.

**P1.** As compared to transaction-based reputation mechanism, subjective aggregation reputation mechanism enables greater community knowledge.

**P2.** As compared to subjective aggregation reputation mechanism, objective aggregation reputation mechanism enables greater community knowledge.

**P3.** As compared to subjective aggregation reputation mechanism, dimensional reputation mechanism enables greater community knowledge.

In order to model the community in which the mentioned mechanisms are applied, we need to consider the community specific attributes which can have an effect on knowledge performance of the community. We mostly rely on KS and social networks literature tied with existing agent-based models to extract such attributes. Based on prior literature and modeling considerations we conclude to include the following three attributes as community specific attributes:

### 3.2. Network density

Based on Scott’s seminal work [20] in social networks, network density is defined as the degree of completeness of a graph. In other words, in a network of nodes, the ratio of total links between nodes to the total number of all possible links indicates network density. This attribute affects the average number of neighbors from whom each member can acquire knowledge, and so we include this variable in our analysis. Greater density, and hence greater neighbors from whom to acquire knowledge, increases the chances of each member to exploit the best value of knowledge. Moreover, more neighbors can increase the effect of interaction-dependency as it increases the likelihood that members would need to decide between two or more neighbors with the same reputation signal. This may increase variability in knowledge acquired, and worsen community-level knowledge performance. Thus, direction of network density influence on community’s knowledge performance is equivocal since opposing causal loops coexist to predict its effect on knowledge performance. Such complexity of opposing causalities can be harnessed by agent-based simulation techniques [1].

**P4.** Network density associates with knowledge performance of community, but direction of such association depends on complexity reduction outcomes of simulation.

### 3.3. Knowledge complexity

Knowledge complexity is defined as the number of bits in which knowledge can be packaged [13]. This definition is closest to our abstraction of knowledge dimensions. We assume that the complexity of knowledge may affect dimensionality and interaction dependency effects. It is obvious that the more dimensions of knowledge there are, aggregative signals are less representative of each dimension’s value and as a result we expect dimensionality to be more of a problem when complexity of knowledge increases. Further, an increase in dimensions increases the number of needed interactions and as a result, interaction dependency can be highly resonated when complexity of knowledge increases. Like network density, the direction of knowledge complexity effects on knowledge performance of the community is not predictable due to coexistence of two opposing causal loops.

**P5.** Knowledge complexity associates with knowledge performance of community, but direction of such association depends on complexity reduction outcomes of simulation.

### 3.4. Learning rate of members

Based on March’s seminal article [17], the learning rate of members of a community is effective in exploitation of members’ knowledge. Lower learning rates are associated with greater possibilities of exploitation, thereby enhancing knowledge performance of the community. In fact, it was shown that in communities with greater learning rates, equilibrium is achieved faster; however, this happens at the expense of leaving some potential knowledge owners under-exploited. As this attribute is relevant to our dependent variable (community knowledge
3.5. Size of community

Although size of community is not a central interest of this paper, we include it as a control variable. Some agent based simulation models used fixed numbers of agents in their models [15], but we vary this modeling variable to gain more robust results. Varying the size of community helps us find out whether the number of agents affects our variables of interest. This can be a potential contribution of our study as it sheds light on practice of fixed numbers of agents in dominant agent-based modeling research.

We also explore possible interaction effects between community-specific attributes and various reputation mechanisms. We also seek to understand how the difference between performances of reputation mechanisms depends on knowledge complexity and network density. These aspects seem vital as they can provide valuable contingent information about proper and cost efficient reputation mechanism design in different types of communities. Overall, our research model can be summarized and illustrated in Figure 1.

![Figure 1. Research model](image)

4. Methodology

Knowledge of individuals is modeled as a multi-dimensional entity with each dimension being 1, 0 or -1. 1 indicates a true belief, 0 indicates no belief and -1 indicates a false belief about that dimension of knowledge. So, for individual $i$, $K_{ij}$ denotes value of $j$th dimension of knowledge. We assume that there $m$ dimensions of knowledge for individuals and $n$ members form the community. So based on what we have described before, knowledge complexity is operationalized by $m$, and as the $m$ increases, knowledge complexity increases. Further, size of community is manipulated by $n$, as number of community members. Network density is operationalized on our model by a variable called node-degree which determines how many connected neighbors each member has in the community. Network density of 1 requires that node-degree is set at $n-1$. Learning rate is operationalized by a variable $p$ that varies between 0 and 1. For simplicity, this variable is constant for all members of the community.

Knowledge is acquired in each specific dimension and the chance of learning that acquired knowledge is equal to $p$ in each interaction. Members of the community acquire knowledge from one of their neighbors with the highest reputation signals. If knowledge is acquired and learned, the member provides feedback which is incorporated to update the reputation signal of the member from whom knowledge is acquired. The simulation terminates when no member can find a connected neighbor from which to acquire knowledge. Community knowledge performance is calculated as the sum of the values of knowledge dimensions for all individuals divided by the possible maximum of the sum of the value of knowledge dimensions for all individuals which is $m*n*1$. The reputation signal for each member is calculated as follows: $k_{ijz}$ denotes knowledge of member $i$ in dimension $j$ acquired by individual $z$. $k_{ijz}$ equals to 1 if that knowledge is acquired and learned and is 0 if the acquired knowledge is not acquired or is acquired and not learned. The subjective aggregation reputation of member $i$, $R_i$ is calculated as follow:

$$R_i = \sum_{z=1}^{n} \sum_{j=1}^{m} k_{ijz} * k_{ij}$$

Transaction-based reputation is calculated as follows:

$$R_i = \sum_{z=1}^{n} \sum_{j=1}^{m} k_{ijz}$$

Objective aggregation reputation is calculated as follows:

$$R_i = \sum_{j=1}^{m} k_{ij}$$

Dimensional reputation of dimension $j$ for individual $i$, $R_{ij}$ is signaled as follows:

$$R_{ij} = \sum_{z=1}^{n} k_{ijz} * k_{ij}$$

Finally, the community knowledge performance is calculated as follow:

$$CKP = \sum_{i=1}^{n} \sum_{j=1}^{m} k_{ij}$$

4.1. Experiments

As we intend to test for effects of three community-level attributes and reputation mechanisms on community knowledge performance, we designed a factorial experiment. We varied the level of network
density and community learning as high, medium, and low. Knowledge complexity is varied for low and high levels and size of community is varied by three levels of high, medium, low. In each block of our factorial design we ran each mechanism 15 times. Although such design only allows us to observe three levels of each variable, it enables us to study the effect of more than one attribute at a time. Such full-factorial design allows us to use regression models with full interaction terms [12]. Yet it provides only a very coarse and linear estimation of the true underlying response surface. A regression model fitted to this design can thus point in the direction of a factor effect and factor interactions but it does not allow us to capture the full range of complex model behavior.

5. Results

To test our propositions, we follow our described factorial experiment with 216 blocks and 15 runs of the simulation in each block. To simulate the described model we used NetLogo 4.1.3 and did our 3240 of runs in the experiment blocks. Such design enabled us to test for main effect of different reputation mechanisms (two currently used and two suggested) and also the main effect of knowledge complexity, learning rate, network density and size of community on community’s knowledge performance. Further, the orthogonal design of blocks enabled us to run our analysis on interaction effect of knowledge complexity, learning rate, network density and size of community with different reputation mechanisms on community’s knowledge performance. Such interaction effect analysis informs us on how interaction dependency and dimensionality effects differ in different settings of a knowledge community. Table 1 provides the results of OLS analysis on our data set. In this table, we report beta coefficients of an OLS output and stars indicate significance of the coefficients. Significant coefficients at 0.01 significance level are triple starred and those significant at .05 level are double starred. Single stars indicate a significant coefficient at 0.1 significance level. We dummy coded the reputation mechanism, as objective aggregation was the benchmark mechanism and other mechanisms are compared to that. This choice of benchmark best enables us to test our intended propositions. As table 1 shows, both subjective aggregation and transaction-based mechanisms perform worse comparing to objective aggregation mechanism in which interaction-dependency is remedied. Also, a close look at standardized coefficients in the regression model for subjective aggregation (-.485) and transaction-based mechanism (-.888) reveals how big the effect of interaction dependency is. This is an important finding as it shows how huge underexploited knowledge of a community can be if problems of interaction dependency or dimensionality of knowledge are not solved in peer-to-peer knowledge communities. Results of standardized coefficients show that transaction-based mechanisms underperform even more than subjective aggregation methods of defining reputation. Overall, we can argue that the best performing mechanism is a mechanism which resolves the interaction-dependency issue. Our results show that addressing dimensionality of knowledge significantly is less effective than addressing the interaction dependency of peer-to-peer communities through an objective aggregation method of evaluating reputation. (Standardized coefficient of dimensionality comparing it to objective aggregation is negative and significant). So far we have been able to approve our first three propositions.

Now, we can study the effect of community attributes on its knowledge performance. Starting with learning rate, we can observe that in fact our model is detecting that higher learning rates are not significantly associated with lower knowledge performance. However, a closer look at interaction effect of learning rate and reputation mechanisms reveals that indeed higher learning rates make performance of subjective aggregations worse than objective aggregation and dimensionality mechanisms. This proves March’s findings in presence of some reputation mechanisms while our findings suggest that the effect of learning rate of members on exploitation of a community’s knowledge should be contingent to the pattern by which members exploit knowledge. Further, OLS results show that more dense networks are associated with higher levels of performance in community (standardized coefficient of network density is .271 and significant at 0.001 level of significance). Further, the interaction effect results suggest that higher network density improves performance of subjective aggregation comparing to objective aggregation mechanism.

Knowledge complexity also proves to worsen performance of peer-to-peer knowledge communities (standardized coefficient is -.057 and significant at 0.001 level of significance). In addition, positive signs of interaction effect of knowledge complexity and dimensional and transaction-based reputation mechanisms suggest that objective aggregation performs worse when complexity of community’s knowledge increases. It can also show that under condition of higher knowledge complexity, salience of dimensionality of knowledge increases relative to interaction dependency.
Finally, size of communities appears to have a negative significant effect on community’s knowledge performance at level of significance of 0.05.

6. Discussion

Based on our study results in section 5, we successfully showed that dimensionality of knowledge and interaction-dependency of peer evaluations are indeed effective factors which can influence community knowledge performance. Although the suggested reputation mechanisms were fully at an abstract level, they provided suitable benchmarks to show how a shift in optimizing reputation mechanisms towards problems of dimensionality and interaction-dependency of peer evaluations can almost double performance gains of a community. It is worth mentioning that designing reputation, like other features of a community, incurs considerable costs. While providing mechanisms to count simply the number of transactions is supposed to be the cheapest solution, circulating peers’ evaluations needs more sophisticated and expensive technologies. We assume that our remedies are incurring costs, which should be taken into consideration at different situations. To begin with, dimensional mechanisms need exploration of appropriate dimensions of knowledge in a community. This step requires research budgets as well as extensive time to exploit optimized number of dimensions which are orthogonal and can suitably shape reputation scores. Such costs are compensated in community configurations in which switching from a subjective-aggregation mechanism to a dimensional mechanism has pay-offs greater than mechanism implementation costs. Specifically, our results indicated that dimensionality provides more pay-offs when community members are less connected.

On the part of objective aggregation, the costs seem to be more salient. In order to be able to have an objective evaluation of knowledge value, standardized tests should be acquired and members of community should go through continuous evaluation in order to update such reputation signals in the community. While our analysis suggests little difference between objective aggregation and dimensional mechanism, a detailed cost analysis can be beneficial to decide with which mechanism a community can optimally raise its pay-offs. Like dimensional mechanism, it was shown that objective aggregation mechanisms can generate larger pay-offs when they are replacing subjective aggregation mechanisms in networks with low density. Although our modeling was at a high abstract level, future studies can translate our two suggested mechanisms guidelines into actual design functions which can be combined, applied and used by current peer-to-peer KS technologies. For the sake of simplicity, our model neglected specific technical issues of designing dimensional or objective aggregation mechanisms. However, we believe such simplicity was needed in order to show how addressing those two issues can potentially help enhancing performance of a knowledge community.

Aside from our core hypotheses about reputation mechanisms, our results revealed insights about the effect of community characteristics on community knowledge performance. First, we found that knowledge complexity can hinder community outcome. This can be used by COP designers to make sure that knowledge complexity of community is at a level which can be managed by current reputation mechanisms concerning density and learning rate of members. Second, we found out that network density increases outcomes of community. However, we suggest this finding should be interpreted with caution since our 3*3*4*2 design does not enable us to detect non-linear relationships between variables.

A close look at results reveals that dimensionality becomes more salient when knowledge complexity increases. In fact, when the dimensions of knowledge increase, the amount of valuable signal reduced as a result of aggregation increases. Such increase in loss of information dimensions makes problem dimensionality more salient.

Finally, and unlike March’s finding, we found that a greater learning rate is not always associated with lower community performance. March [17] indicated that although a lower learning rate leads to later occurrence of equilibrium, the performance will be higher as a result of better exploitation of the community’s knowledge. However, applying different mechanisms to promote and diffuse knowledge, our study found that there are contingencies under which March’s findings hold. According to our results, lower learning rate associates with higher equilibrium performance only in case of subjective aggregation and transaction-based mechanisms. It can be argued that in less intelligent ways of promoting knowledge, an increase in chances of looking for knowledge by trial and error can increase the chances of obtaining higher community knowledge performance. In such underperformed mechanisms in which signals about knowledge dimensions are not provided and subjectivity biases validity of aggregate evaluations, rate of mistakenly choosing a non-trustworthy source is higher. Thus, in order to not be trapped in suboptimal performance, community members need to expand the exploitation spans. This exploitation then can be processed through low learning rates. However, our results show that when interaction dependency and fallacy of dimensionality are remedied, the community
does not need such time taking exploitation by low learning rate to reach optimal level of knowledge performance. As has been discussed, one of the major drawbacks of using agent-based modeling as the sole method of research is that external validity of the results are at question [16]. However, we believe like any other research, choosing this method is a matter of trade-off. In fact, we tried to reduce complexity of a phenomenon which we believe has not been discussed in relative literature of peer-to-peer KS communities. Such complexity reduction needed structured bottom-up effort which made agent-based modeling and simulation a desirable method to answer this study’s question. However, we do believe that follow-up field studies to test our propositions can be done to triangulate reliability of our study results.

Further, we were not able to test robustness of our results on communities with more than two hundred members. However, we realize that most real KS communities may consist of more than two hundred members and thus we encourage studies on both extending the simulation on more than two hundred agents and practical field studies on communities with large membership sets. We believe that such studies can enhance internal and external validity of our results respectively.

We believe our research contributes to peer-to-peer KS body of literature in three distinct ways. First, it successfully shows the effect of neglecting knowledge dimensionality and information reduction effects of subjective evaluation aggregation. While prior papers on peer-to-peer KS largely focus on remedying cognitive biases and use single criterion methods, our research shows that even in an ideal world in which a single criterion method of defining reputation is sufficient and peers in the community are not subjected to cognitive biases, neglecting dimensionality of knowledge can reduce knowledge performance of the community into half its actual potential. Second, we bring up another fallacy of subjective aggregation, which targets subjectivity of such evaluations. We showed that interaction-dependency, like ignorance of dimensionality, can effectively reduce community knowledge performance. Last but not least, we proposed two new community attributes, which interact with reputation mechanisms to enhance knowledge performance of community. We showed that network density and knowledge complexity can change the effect of ideal reputation signals in a KS community.

References


Table 1. Results of OLS analysis

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<th>Variables</th>
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<th>Direct and indirect effect model</th>
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<td>Size of Community</td>
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<td>Learning Rate</td>
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<td>Adjusted $R^2$</td>
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<td>Change in $R^2$</td>
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