Exploring the Role of Learning in Crowdsourcing Creativity: The Value of Idea-Building in the Crowd

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Short Paper

Introduction

Who should we turn to for creative thinking? Recent research suggests that due to the diversity that crowds can offer (Chiu et al. 2014; Rosen 2011), the crowd is a viable option to create something novel (Afuah and Tucci 2012; Chiu et al. 2014; Howe 2006; Rosen 2011). While diversity can help tasks to be accomplished creatively, creativity theories suggest that creativity also requires domain knowledge (Amabile 1996; Gurteen 1998; Ribière et al. 2012). However, crowds usually consist of novices who do not possess, or acquire, sufficient domain knowledge to fully understand the need for creativity in open calls. Without sufficient knowledge, crowd members may not be able to understand the tasks or may be unable to strategically search for the appropriate knowledge that would generate creativity (Gurteen 1998; Ribière et al. 2012).

To date, the knowledge requirement for working creatively on a crowdsourcing project has been assumed to exist but its effects on task performance have been understudied. Prior literature (e.g., Afuah and Tucci 2012; Gerber 2014; Kittur et al. 2013) generally assumes that crowd members can match their knowledge levels with the creative needs of the task. For example, Afuah and Tucci (2012) suggested that crowd members automatically search for tasks based on their specialties, and this process of ‘self-selection’ reduces the time and effort required by companies to match crowd members with tasks. Taking this assumption further, several studies suggested that the collective and distributed intelligence can self-organize an entire economic system (Gerber 2014; Kittur et al. 2013). Nonetheless, previous studies overlooked the importance of knowledge as the precondition for achieving creativity from the crowd’s diversity.

To address this research gap, this paper focuses on an emerging form of crowdsourcing whereby members learn about their task by interacting with others. It argues that crowds can be as creative as experts if members participate in this learning process. Since the inception of crowdsourcing, creativity has evolved from idea generation to idea building. Idea generation refers to the process by which individuals submit their original work independently, for example via Amazon Mechanical Turk. Idea building describes the process in which members build on each other’s work, for example, by way of Thingiverse, Scratch, etc (Buhrmester et al. 2011; Kyriakou et al. 2017; Hill and Monroy-Hernández 2012; Resnick et al. 2009). Idea building in the crowd can serve as a vehicle, which enables individuals to learn and to gain the knowledge required for creativity. Such collaborative and shared learning can elevate individual member’s knowledge of the target subject. Therefore, for tasks that are unfamiliar to members it is possible for individuals to gain the required knowledge regarding the tasks by building upon each other’s ideas. Hence, the purpose of this research is to compare the performance of creativity tasks by crowd members in three settings: 1) when ideas are generated by crowds, and 2) when crowd members build on each other’s ideas, and 3) when ideas are generated by experts (as the benchmark).

Based on prior literature, we theoretically explained the effects of learning in the context of crowdsourcing creativity. We then conducted an online experiment in which we could directly observe and identify causality among variables (Mosteller 1990; Winston 1990; Winston and Blais 1996). In particular, we sought to collect ideas that had been built from the collective ideas of individuals in crowds, and for this process we organized two rounds, in which crowds from Amazon Mechanical Turk (MTurk) were invited to build on, and supplement, the ideas of others. In order to collect ideas generated by experts, we requested PhDs in the field of computer science to develop relevant ideas; and to test the creativity of crowds who submit ideas independently we asked an MTurk crowd to produce their own ideas independently. For idea collection, we purposely selected the task that did not match the crowd’s knowledge (the design of a cyber security channel).
Literature Review and Hypothesis Development

People acquire knowledge through learning, through constantly accessing and integrating new knowledge. Many studies have examined different techniques for acquiring knowledge and understanding from others, either via explicit formats including texts, audios, videos, etc, or by way of implicit learning from mentors (Morris et al. 2013; Smith et al. 1993; Yu et al. 2014). In general, crowdsourcing has evolved with the crowd addressing the open call independently and individually – that is, without building on each other’s ideas. This has commonly taken the form of competitions where members submit ideas either individually or in small teams. An instance was provided by Netflix (Bennett and Lanning 2007), which offered a reward of one million dollars to an individual or team that increased the accuracy of its rating algorithm by 10%. In contrast to this individualised approach, the latter form involves members collaborating organically to address an on-going open call (Malone et al. 2010). That is, crowd members proactively interact with other crowd members in addressing these tasks. For instance, on Wikipedia, members can edit the contributions of others. Many scholars have studied this new form of collective contributions to trace the emergence and evolution of overall creativity that accumulates on crowdsourcing sites (e.g., Hill and Monroy-Hernández 2012; Kyriakou and Nickerson 2014; Resnick et al. 2009). Some researchers have studied how young people generate creative projects via interactions using the Scratch language (Hill and Monroy-Hernández 2012; Resnick et al. 2009). Other studies discuss collective innovation in a 3D printing design-community (Kyriakou and Nickerson 2014).

Several research projects have examined different techniques for increasing the crowd’s capacity to be creative, those studies focusing on the effects on creativity of remixes, modifications, and combinations of contributions from crowd members (e.g., Han and Nickerson 2015; Kaplan and Vakili 2015; Ren et al. 2014). For example, Ren et al. (2014) compared the techniques of modification and combination and their impacts on creativity. Kaplan and Vakili (2015) suggested that distant recombination has a positive impact on both the novelty and economic value of a patent. Other studies have borrowed theories from organizational learning, arguing that adding crowdsourcing as an external knowledge pool can help organizations to learn (e.g., Schlagwein and Bjorn-Andersen 2014). However, the learning effect studied in those papers did not refer to learning among crowd members to increase each other’s knowledge. Specifically, Huang et al. (2014) found that crowd members can learn quickly about their ability to come up with potentially useful ideas, but they learn slowly on matters concerning a firm’s cost structure.

The collaboration of the crowd, consisting of individuals from diverse backgrounds, allows for the emergence of collective knowledge, which can further promote the creation of new ideas and innovations (Lee et al. 2015). The generation of collective knowledge can be achieved through knowledge-sharing and learning processes. On the one hand, knowledge sharing “is a set of behaviors that involves the exchange of information or provision of assistance to others” (Janz and Prasarnphanich 2003) and it occurs when individuals assist and learn from one another to develop new competencies (Yang 2007). As individuals interact with each other, skills and values are mutually understood and knowledge can be transferred (Lave and Wenger 1991). Socialisation entails members interacting with each other (Nonaka and Takeuchi 1995), and in the process information and knowledge are shared. On the other hand, learning through diversity is mainly “about the question as to how the build-up and generation of new knowledge can be improved so as to achieve innovation and flexibility of action” (Andresen 2007). When crowd members interact, and if those members possess different domains of knowledge, this allows learning to occur and new knowledge can emerge. Applied to idea-building in the crowd, the interactions enable members to acquire the required knowledge, to understand the open call, and to suggest possible solutions. In summary, compared to idea generation within the crowd, members in the new form of crowdsourcing can learn from each other to build new ideas so as to overcome the knowledge barrier. Accordingly, H1 is proposed as follows.

\[ H1. \quad \text{In regard to tasks or problems for which crowd members lack sufficient knowledge, the crowd can gain knowledge by building on each other’s ideas. Therefore, their knowledge will increase to a level that is higher than that in the idea generation setting.} \]

Based on Amabile’s theory of creativity (1983), knowledge is important to creativity and many assumed this is the requirement for innovation to happen (Boh et al. 2014). Specifically, the crowd may remix each other’s ideas via combination or modification as they learn from each other. Combination helps generate creative ideas, especially original ideas. Idea combination triggers divergent thinking that explores many
possible solutions. Modifying ideas, in contrast, helps generate incremental ideas that are easy to adopt. Specifically, modification helps narrow down the focus of the outcome. Therefore, once the crowd have acquired relevant knowledge to answer an open call, their creativity will increase. Hence, H2 is proposed as follows.

**H2. In regard to tasks or problems for which crowd members lack sufficient knowledge, the outcomes of idea-building in the crowd are more creative than the outcomes of idea-generation in the crowd.**

**Method**

To test the hypotheses, we conducted an online experiment, the method popularly applied in the crowdsourcing setting (Tarrell et al. 2013; Zhao and Zhu 2014). The experimental method has the following two advantages: first, it enables the researchers to directly observe group differences (Mosteller 1990; Winston 1990; Winston and Blais 1996); second, it can help us examine the effect of stimuli that are isolated from confounding variables. The study was conducted in two steps: the first entailed collecting ideas, and the other assessed and rated the ideas.

**Step 1: Collecting Ideas**

**Learning by the Crowd**

In order to measure creativity in performing a task for which crowd members would have little knowledge we selected a task concerning cyber security (See Table 1). To validate the level of knowledge required in this task, we conducted a pilot study on Mechanical Turk (a crowdsourcing marketplace); we also included PhDs in the field of computer science in the pilot study. Each subject in the pilot study was asked to evaluate either of these tasks on the dimensions of familiarity with, and knowledge of, the topic (Ohanian 1990). After applying a two-sample t-test, we found that for the cyber security task, experts were more knowledgeable than the crowd (p < 0.001). As the answers are self-reported and may suffer from the limitation of inflation, as a baseline effect, we also repeated the same procedure for a task where the crowd have sufficient knowledge to address. This task is related to creating an idea for an iPhone application. Based on a two-sample t-test, we found for this task, experts were as knowledgeable as the crowd (p > 0.1).

<table>
<thead>
<tr>
<th>Table 1. Stimuli Construction</th>
</tr>
</thead>
<tbody>
<tr>
<td>Task Type</td>
</tr>
<tr>
<td>The task that the crowd do not have knowledge to answer</td>
</tr>
<tr>
<td>The task that the crowd have knowledge to answer (the baseline effect)</td>
</tr>
</tbody>
</table>

Moreover, we treated the Mechanical Turk workers as the crowd in that they had different backgrounds and were located worldwide. Each subject was asked to generate a creative idea in response to the issue described in Table 1. In parallel, we asked another group of crowd members, each working independently, to generate an innovative proposal. When all the responses had been collected from this group of crowd members, we randomly presented three to each of another group of crowd members to act as a starting point of reference. Specifically, we provided the following instructions; “Three fellow Mturkers have submitted the following three ideas respectively to help this company”, and then asked the latter group of members to generate a creative idea to help the company. We repeated the process of requesting other crowd members for ideas for two more rounds.
Each crowd member only participated once by providing one proposal. In addition, we collected ideas from experts, PhDs from the field of computer science, as the benchmark. Therefore, we collected a relatively small number of crowd solutions in order to have a sample size as comparable to the limited number of experts’ solutions. Table 2 summarizes the information provided by subjects.

<table>
<thead>
<tr>
<th>Task Type</th>
<th>Group of Subjects</th>
<th>Number of Subjects</th>
<th>Average Age</th>
<th>Percentage of Male</th>
</tr>
</thead>
<tbody>
<tr>
<td>The task that the crowd does not have knowledge to answer</td>
<td>Experts</td>
<td>17</td>
<td>30.23</td>
<td>70%</td>
</tr>
<tr>
<td>Idea generation in the crowd</td>
<td>50</td>
<td>31.62</td>
<td>48%</td>
<td></td>
</tr>
<tr>
<td>Idea building in the crowd: Stage 1</td>
<td>50</td>
<td>30.22</td>
<td>52%</td>
<td></td>
</tr>
<tr>
<td>Idea building: Stage 2</td>
<td>50</td>
<td>34.67</td>
<td>44%</td>
<td></td>
</tr>
<tr>
<td>Idea building in the crowd: Stage 3</td>
<td>50</td>
<td>34.89</td>
<td>42%</td>
<td></td>
</tr>
<tr>
<td>The task that the crowd have knowledge to answer (the baseline effect)</td>
<td>Experts</td>
<td>23</td>
<td>30.78</td>
<td>74%</td>
</tr>
<tr>
<td>Idea generation in the crowd</td>
<td>50</td>
<td>31.34</td>
<td>40%</td>
<td></td>
</tr>
<tr>
<td>Idea building in the crowd: Stage 1</td>
<td>50</td>
<td>33.12</td>
<td>56%</td>
<td></td>
</tr>
<tr>
<td>Idea building: Stage 2</td>
<td>50</td>
<td>33.37</td>
<td>50%</td>
<td></td>
</tr>
<tr>
<td>Idea building in the crowd: Stage 3</td>
<td>50</td>
<td>22.02</td>
<td>58%</td>
<td></td>
</tr>
</tbody>
</table>

**Measuring Levels of Knowledge**

We asked subjects about their levels of knowledge in relation to the topic, and to do this we applied the measurement scale of expertise developed by Ohanian (1990) (See Table 3). This was done after the participants had completed the tasks.

<table>
<thead>
<tr>
<th>Item</th>
<th>Question</th>
</tr>
</thead>
<tbody>
<tr>
<td>Expertise</td>
<td>How much do you consider yourself as an expert in the domain of the displayed topic?</td>
</tr>
<tr>
<td>Experience</td>
<td>How experienced are you in the domain of the displayed topic?</td>
</tr>
<tr>
<td>Knowledge</td>
<td>How knowledgeable are you in the domain of the displayed topic?</td>
</tr>
<tr>
<td>Qualifications</td>
<td>How qualified are you in the domain of the displayed topic?</td>
</tr>
<tr>
<td>Skill</td>
<td>How skilled are you in the domain of the displayed topic?</td>
</tr>
<tr>
<td>Familiarity</td>
<td>How familiar are you with the displayed topic?</td>
</tr>
</tbody>
</table>

**Step 2: Rating Ideas**

To test the hypotheses, we focused on the ideas provided by experts, on idea-generation in the crowd, and on stage 3 in the idea-building group (Ren et al. 2014); that is, the groups listed in bold font in Table 2. As a result, each of the 217 ideas on cyber security and the 223 ideas on iPhone application was evaluated by three experts (PhDs in the field of computer science) as well as by three crowd members (Mollick and Nanda 2015). Each crowd member only rated one idea, but each expert independently rated all 400 ideas (that were randomly sorted). The experts and crowd members who conducted the evaluations were unaware of the source of each idea.

Subjects evaluated ideas according to the novelty dimension of creativity. We followed the measurement scale that had been synthesized and developed by Dean et al. (2006) from prior literature (e.g., MacCrimmon and Wagner 1994; Plucker et al. 2004). Specifically, each subject was asked to answer five questions on a 7-point Likert scale (Table 4) and we averaged each subject’s answers to measure novelty.
For analysis, we averaged the ratings from both experts and members of the crowd to address the conditions where subjects were asked to answer the cyber security open call and the iPhone application open call respectively, the inter-rater reliability being 0.69 and being 0.71, which is consistent with the standards indicated by prior literature (LeBreton and Senter 2008).

<table>
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<tr>
<th>Table 4. Measurement Scale for Creativity</th>
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<tbody>
<tr>
<td>Novelty</td>
</tr>
<tr>
<td></td>
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</tbody>
</table>

In total, 1603 subjects participated in our study either by providing an idea or by rating ideas. Experts all possessed PhDs in the field of computer science. In contrast, all crowd members were United-States based Mechanical Turk workers who had approval ratings (as tabulated by Amazon) higher than 95%: their backgrounds were consistent with demographic results from other studies (Kittur 2008; Ross et al. 2010).

**Results**

H1 was supported. Applying independent-sample t-tests, the results confirmed the learning effect in the group of idea building in the crowd. In regard to tasks for which crowd members initially have insufficient knowledge, as the process of priming other crowd members with ideas proceeds from Stage 1 to Stage 3 the crowd members’ knowledge level increases significantly to a level higher than that in the idea generation condition ($p < 0.001$; $p < 0.001$), as shown in Figure 1. Interestingly, experts’ knowledge is still higher than that from Stage 3 in the idea building condition ($p < 0.001$). As a comparison, there is no significant difference in terms of knowledge level among the three conditions for the tasks for which crowd members have sufficient knowledge ($p > 0.1$).

Moreover, H2 was supported as well. We conducted multiple independent-sample t-tests to compare the creativity performances of ideas of experts, of idea-generation by the crowd, and of idea-building in the crowd (See Figure 2). Figure 2 shows that ideas generated by idea-building in the crowd are more novel than those of idea-generation in the crowd (2.83 versus 2.45, $p = 0.013$). However, experts’ ideas were not more novel than the proposals from idea-building in the crowd (3.1 versus 2.83, $p = 0.296$).
Discussion

Overall, the research results show that when crowd members do not initially have the necessary knowledge to complete the creativity task they are able to learn and to increase their knowledge level by interacting with other members. Once members gain relevant knowledge, the inherently diverse nature of crowds can lead to outcomes that are comparable with the outcomes produced by experts. Next, we further investigated idea-building in the crowd by specifically considering how ideas were supplemented by the contributions of others in the crowd and by conjecturing on ways to amplify this learning effect for idea-building in the crowd.

On the one hand, we detected two patterns in the way crowd members utilized the ideas they were exposed to for creating new ideas. Some members tend to modify or combine elements of other ideas to generate better alternatives. In some instances, we found that crowd members were inspired by other ideas and thus devised an alternative. This is consistent with creativity literature that states that ‘idea combination’ helps generate creative ideas (e.g., Fleming et al. 2007; Hargadon 2003; Schumpeter 1961), and triggers divergent thinking that explores many possible solutions (Ward 2001); whilst ‘idea modification’ may produce ideas that are highly creative (e.g., Collins and Loftus 1975) and it may help to narrow the focus of the outcome (Buxton 2010).

On the other hand, our findings show that if the crowd lacks the knowledge to perform a creativity task, they can learn from the ideas of other members. While their ideas may be as creative as those provided by experts, their knowledge levels are still lower than those of experts on the topic (Figure 1, p < 0.001). Arguably, if we can create an environment where crowds can increase their learning, their outcomes may be even more innovative. However, regarding open calls, crowds may not be able to achieve this with further interactions among themselves because members essentially are customers who gain knowledge through everyday experiences. Moreover, they may be unfamiliar with the R&D details that eventually produce the product. The crowd members’ organic interactions may arrive at a limit on the knowledge capacity that they can eventually learn from each other. One way to avoid such a restriction would be to include inputs from experts into the deliberations of crowds. Such an artificial intervention may help accelerate the learning in general, and it could provide specific knowledge details that the crowd would not otherwise encounter (Nonaka and Konno 1998). This is consistent with the SECI model (socialization, externalization, combination, and internalization) devised by Nonaka and Takeuchi (1995). Perhaps some intervention by means of a learning tool could increase the generated knowledge of the crowd (Nonaka and Konno 1998). As a result, the novelty of the outcome of idea building in the crowd may eventually increase to a level more creative than that of experts.
Limitation and Future research

All research has limitations. First, a limitation of this paper is the measurement of idea-building in crowds. Specifically, crowd members build ideas on the ideas of other novice users, but in many crowd-based settings experts can also be part of the crowd. For example, in a user-created design-sharing platform that encourages people to discover, share, and develop 3D objects, passionate hobbyists who are experts in their fields are among contributors. In our experiments, we isolated experts from our crowds so as to provide a point of comparison with the performance of novices. It would be interesting to see if our findings can be generalized to platforms where the crowd interacts with each other and with other experts.

Another limitation is how crowd ideas were integrated. Prior literature has suggested the following method for measuring the crowd’s performance: the average of individual crowd ideas and top ideas (Yu and Nickerson 2011). In this study, we used the average. We argue that an average is a widely-accepted way of measuring performance. Also, a t-test is commonly used to compare group performances and thus is highly applicable to this study. Even so, we call for studies that can adopt other idea-integration methods so as to study idea-building in the crowd.

Conclusion

This paper makes several contributions to both research and practice. This paper revisits and examines the long-held assumption in crowdsourcing research that diversity of a crowd leads to heightened creativity, and it examines a precondition for the positive impact of diversity; that is, knowledge. To address the research gap, this paper promotes the possibility of a new form of crowdsourcing in which members learn from each other to acquire the necessary knowledge. Moreover, this paper provides empirical evidence to justify the increasing prevalence of crowd collaboration where learning for more knowledge becomes possible via their organic interaction (e.g., Thingiverse, the Climate CoLab, Scratch). For practitioners, strategies are recommended for how crowd creativity can be fostered especially for the type of tasks which they assume would be better undertaken internally within the firm.

References


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