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What You Know and What You Don't Know: A Discussion of Knowledge Intensity and Support Architectures in Improving Crowdsourcing Creativity

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Improving Crowdsourcing Creativity: The Role of Knowledge Intensity and Support Architectures

Short Paper

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Abstract

Building on the componential theory of creativity, we studied how the crowdsourcing creativity support architectures and the task knowledge intensity levels affect the crowd's creativity. Using an online experiment, we found that remixing can trigger the crowd to be more creative than external stimuli and using either architecture triggers the crowd to be more creative overall. Also, the crowd is more creative in solving low-knowledge-intensity tasks than in solving high-knowledge-intensity tasks. Interestingly, regardless of the knowledge intensity levels of tasks, crowdsourcing support architectures have a significant impact on the crowd's creativity. Therefore, our paper contributes to the crowdsourcing literature on promoting crowd creativity and provides practical implications on solving societal challenges, especially large-scale problems.

Keywords: Crowdsourcing creativity, external stimuli, remixing, domain knowledge

Introduction

Crowdsourcing has become a powerful alternative source of creativity for organizations. However, prior research has shown that the creativity of the crowd-based solutions may be inadequate (Bayus, 2013; Oppenlaender et al., 2020). For example, the crowd often fails to offer well-considered solutions that incorporate multiple perspectives (Schenk & Guittard, 2011), and the crowd members tend to act autonomously when developing a solution rather than elaborating on the ideas of others, resulting in only incremental improvements rather than novel solutions (Madsen et al., 2012). To improve the crowd-based solutions, previous research mainly focused on the characteristics and motivations of the participants (Ren et al., 2017; Zou et al., 2020), task design (Chandler & Kapelner, 2013; Zheng et al., 2011) and the quantity of contributions (Füller et al., 2011). However, research on the design of the crowdsourcing software, architectures, user interfaces, and practices to motivate creative contributions has been scarce (Leimeister et al., 2009; Majchrzak & Malhotra, 2013). To fill this research gap, we use a well-studied theory that explains individual creativity and apply it in the context of crowdsourcing creativity.

The componential theory of creativity (Amabile, 1983) suggests three within-individual components that are crucial to creativity: motivations, creativity-relevant processes, and domain knowledge. Motivation is described as the reason for performing a task or solving a problem. The motivations of crowdsourcing participants have been well explored in the prior literature (Acar, 2019; Chan et al., 2021). Creativity-relevant processes include individuals' cognitive styles and characteristics such as being able to apply different perspectives on problem-solving; these characteristics affect response generation in the creative process and can be influenced by creativity support tools or architectures (Chavula et al., 2022; Frich et al., 2019). For example, studies have investigated virtual reality (VR) as a tool that can be applied to enhance creativity (Bonnardel & Pichot, 2020; Lee & Chau, 2019). In this vein, we focus on the effects of two crowdsourcing support architectures (design elements or creativity support tools that encourage and integrate ideas/contributions made by participants (Frich et al., 2019; Majchrzak & Malhotra, 2013) on the creativity of crowd contributions: (i) external stimuli and (ii) remixing. External stimuli, a limited number of ideas that can facilitate crowd participants' exposure to the different perspectives of the problem, can enhance the creativity of crowd-based contributions (Goucher-Lambert & Cagan, 2019). Systems that allow "remixing" – modifying and recombining others' work have also been found to support crowd creativity and lead to innovative solutions (Hill & Monroy-Hernández, 2013; Nickerson, 2015)

Lastly, domain knowledge is the professional skills of an individual, such as knowledge and expertise in a specific area. They can help individuals establish and activate stored knowledge and search for possible problem-solutions for creativity (Weisberg, 1999). Few studies that focused on creativity and innovation research have found evidence of positive relationship between domain knowledge and creativity (Jeppesen & Lakhani, 2010). However, it has also been suggested that high levels of domain knowledge can actually be restraining to creativity, leading to a declining positive relationship (Sternberg et al., 1997). Thus, in this study, we look at tasks with two different knowledge intensities (high versus low): For some tasks, the crowd may be equally knowledgeable as professionals or experts. For example, these generalist tasks might include designing an everyday item (e.g., chair), how to improve the Starbucks experience or collecting ideas for a smartphone app to connect with local municipalities (Hossain & Islam, 2015; Yu & Nickerson, 2011). Other tasks are more knowledge-intensive and require specialist deep knowledge, such as generating ideas for fighting global climate change or reducing poverty (Malone et al., 2017).

Therefore, in this study, we aim to answer three research questions:

1. Related to the component of domain knowledge: How does the knowledge intensity of tasks affect the crowd's creativity?
2. Related to the component of creativity-relevant processes: How do crowdsourcing support architectures ((i) external stimuli and (ii) remixing) affect the crowd's creativity?
3. Related to the interaction of both components: How does the knowledge intensity of tasks interact with crowdsourcing support architectures in affecting the crowd's creativity?

To answer these questions, we conducted an experiment on Amazon Mechanical Turk (AMT), an online crowdsourcing platform where requesters post tasks and workers self-select which tasks to perform for pay. As our crowdsourcing tasks, we focus on societal challenges. In a global context of resource scarcity, many different incentives and motivations might exist to pursue product, service, or process innovations, but only very few incentives exist to pursue innovations for societal problem solving (Callaghan, 2014). Unlike specialized tasks and specialized interests, societal challenges are inherently global, and they affect everyone in similar ways - therefore it would be at least in the common interest of all crowd members to resolve them. In addition, solving a societal challenge is different than the tasks in other innovation contexts because societal challenges have many different stakeholders and there is no single solution or formulation of the problem; thus, there are no right or wrong answers to these issues (Han et al., 2020).

Conceptual Foundation and Research Hypotheses

The Componential Theory of Creativity - Knowledge Intensity

Knowledge is a critical factor within the creative process, as it empowers individuals to produce novel insights (Amabile, 1983; Candy & Edmonds, 1997). Existing knowledge determines the potential pathways when humans search for a creative solution and is a fundamental prerequisite for creativity (Couger et al., 1993). Newell and Simon (1972) refer to individuals' existing knowledge base as their network of possible wanderings - a problem space that determines the bounds of the possible solution pathway. Similarly, Weisberg (1999) views creativity as a cumulative process of building on existing understanding. Fleming (2001) suggests that if inventors are familiar with the knowledge domain, they will be more able to generate ideas that are creative. Therefore, we propose:

H1: The crowd will generate ideas that are more creative when they face tasks of low knowledge intensity than when they face tasks of high knowledge intensity.

Crowdsourcing Creativity Support Architectures

We argue that creativity relevant processes can be triggered by different crowdsourcing architectures. Traditionally, crowdsourcing architectures only allowed the participants to perform the crowdsourcing task independently and individually – that is, without building on each other's ideas. This commonly takes form of competitions where participants submit their ideas without seeing other's contributions (Leimeister et al., 2009; Morschheuser et al., 2019). Another common type of crowdsourcing architecture requires participants to post their ideas as a new discussion thread, in which following participants may then contribute by adding comments (Majchrzak & Malhotra, 2013). However, since such architecture requires ideas to be posted as new threads, the comments tend to focus primarily on refining a posted idea rather than recombining existing posts into new ideas. At the end, through these architectures the final ideas rarely reflect multiple perspectives because they lack combination and integration (Wright, 2013).

However, in order to generate creative ideas, idea integration is critical (Okhuysen & Eisenhardt, 2002). Considering some or all dimensions of others' ideas and creating conceptual connections among those dimensions leads individuals to divergent thinking that explores many solutions (Patnayakuni & Ruppel, 2006). Divergent thinking involves switching from one perspective to another, picking unusual associations between different ideas in novel ways (Stokes, 2001). Prior literature has shown how divergent thinking and idea association affects individuals' intelligence and creativity (Gerwig et al., 2021; Sun et al., 2019).

As a major source of creativity, this process of generating associations between different ideas and divergent thinking needs to be supported in various ways (Müller-Wienbergen et al., 2011). In this paper, we focus on the external stimuli and the remixing architectures to explore the divergent thinking triggered by the crowdsourcing support architectures. External stimuli can be implemented by showing existing ideas to idea generators before they start to generate their own creations (Ren et al., 2014; Yu & Nickerson, 2011). External stimuli lead to an increased number of cues in memory, which enhances knowledge activation in memory (Gawronski & Bodenhausen, 2005). In other words, exposure to other crowd members' ideas can help each individual crowd member to activate their knowledge that is accumulated throughout their own experience and consequently can help with divergent thinking. However, the crowd do not necessarily need to use the knowledge in other crowd members' ideas. They may voluntarily apply divergent thinking prompted by external stimuli as they have the *choice to use or not use* the knowledge in other crowd members' ideas.

Unlike external stimuli, remixing architectures have a built-in feature that forces the crowd to re-use knowledge from other crowd members' ideas and to build on them. Normally the remixing architecture can be implemented by creating attribution systems such as the "fork" function in Github and the "remix" function in Scratch (Jiang et al., 2017; Resnick et al., 2009). Thus, remixing can be seen as knowledge reuse for innovation (Armbrecht Jr et al., 2001; Majchrzak et al., 2004). Remixing does artificially force the crowd to use knowledge from other crowd members' ideas, thus increasing the divergent thinking triggered by such support architecture. In other words, the crowd have to apply divergent thinking prompted by remixing as they are *forced to use* the knowledge in other crowd members' ideas. Therefore, we propose:

H2: The crowd who use remixing will generate ideas that are more creative than those who use stimuli.

Moreover, we propose the effects of crowdsourcing support architectures on crowdsourcing creativity are moderated by the knowledge-intensity of the task. For example, the crowd are familiar with a simple task such as collecting ideas for a chair design, therefore any inspiration from other crowd members' ideas can help them utilize meaningful divergent thinking and thus can help with their creativity (Yu & Nickerson, 2011). Conversely, if the task is knowledge-intensive such as generating ideas for designing a skyscraper, any inspiration from other crowd members' ideas may lead them to artificially associate random concepts that are not related to the task at all and thus can hurt their creativity (Ren et al., 2021). While both tasks (designing a chair vs designing a skyscraper) can be considered design tasks, their knowledge intensity is different. Therefore, we propose:

H3: The support architectures will lead crowd to generate ideas that are more creative when the crowd are solving tasks of low knowledge intensity compared to when the crowd are solving tasks of high knowledge intensity.

Research Design

The experiment was conducted on Amazon Mechanical Turk (AMT). Past researchers found that AMT platform assist researchers to collect high quality and replicate classical psychological phenomena (Crowston, 2012; Jia et al., 2017). In return for a nominal compensation, in total 230 AMT workers (MTurkers) participated in the different phases of the experiment. While MTurkers self-selected into participating in our experiment, we restricted participation to MTurkers with high reputation (above 95% approval ratings) (Peer et al., 2014) and U.S. as their location for language purposes.

Experimental Phase 1: Determining high and low-knowledge intensity challenges

Phase 1 of our experiments is related to determining high-knowledge intensity and low-knowledge intensity societal challenges, so that we can use those challenges in the next phases to test different support architectures. The most universal and widely adopted societal challenges defined by different foundations are the Sustainable Development Goals of the United Nations (George et al., 2016). Therefore, we used those societal challenges as our starting point of Phase 1. We recruited 30 MTurkers to evaluate the knowledge intensity of each societal challenge topic. Following self-reporting practice used commonly in the crowdsourcing studies (Ren et al., 2021), we asked each MTurker to answer the following two questions based on a 7-point Likert scale as a pretest to evaluate the knowledge intensity of each task that the crowd perceives on average: 1) How knowledgeable are you with this topic? (1- not knowledgeable at all and 7- very knowledgeable); and 2) Given your background knowledge in this topic, how easy is it for you to come up with new ideas on how to address this societal challenge? (1- very hard and 7- very easy). Based on the MTurkers' evaluations, we identified "birth mortality" as our high knowledge-intensity societal challenge topic and "obesity" as our low knowledge-intensity societal challenge topic.

Experimental Phase 2: Soliciting Initial Ideas

In this experimental phase, there are two conditions: low knowledge-intensive task with no stimuli or remixing (Condition1), high knowledge-intensive task with no stimuli or remixing (Condition2). We recruited 50 MTurkers to generate ideas under each condition. We asked each MTurker to generate a creative idea that can address the listed societal challenge. The idea word length was required to be more than 100 words. We also collected each MTurker's demographic information, including gender (Female:53, Male:47), native language (English 92, Chinese: 8) and highest education level (High School: 31, Bachelor: 60, Master degree and above: 9).

Experimental Phase 3: Varying Participation Architecture

We examined four conditions of support architectures on different knowledge-intensive tasks: low knowledge-intensive task with stimuli (Condition 3), low knowledge-intensive task with remixing (Condition 4), high knowledge-intensive task with stimuli (Condition 5) and high knowledge-intensive task with remixing (Condition 6). For each condition, we recruited 50 MTurkers. In Condition 3 and Condition 5, we provide 3 random ideas generated from experimental phase 2 as examples for each participant and ask the participant to generate a creative idea. In other words, each participant can face a different set of three random ideas. In Condition 4 and Condition 6, we provide 3 random ideas generated from experimental phase 2 for each participant and ask the participant to combine and modify these ideas and generate a creative idea. In all conditions, the final idea needs to be more than 100 words. For each participant, we also collected the demographic information, including gender (Female: 105, Male: 95), native language (Bengali: 1, Chinese: 5, Italian: 1, English: 193) and highest education level (High School: 46, Bachelor: 72, Master degree and above: 18).

Experimental Phase 4: Idea Evaluation

Consistent with prior crowdsourcing research evaluation of crowd generated ideas, we measured the crowd members' creativity based on the "novelty" and "practicality" of their generated ideas, with a single measure for each dimension (Kornish & Ulrich, 2011; Ren et al., 2021). We invited two experts (two medical doctors who have experience in both topics) to evaluate all ideas under different conditions based on their novelty and practicality. These ideas were sorted randomly. Therefore, neither expert was aware of the conditions of our experiment and didn't know the source (condition) of the ideas they evaluated. Both experts met with one of the authors to discuss how to evaluate the ideas. The author instructed the experts that an idea's feasibility and potential market demand should be accounted for when the idea is being evaluated for practicality (Luo & Toubia, 2015). For evaluation of idea novelty, the experts were instructed to evaluate each idea in relation to how uncommon it is based on their expertise/experience in the area (not how uncommon it is in the overall population of ideas) (Dean et al., 2006). Creativity was calculated as the average of both dimensions. Each expert evaluated the same initial 10 ideas, then discussed their evaluation. Once reaching a consensus on the initial ideas, the experts continued to evaluate the rest of the ideas on their own. The interrater reliability of experts' evaluations (calculated using Average Cohen's kappa) was 0.77, indicating a good degree of reliability (Orwin & Vevea, 2009). Based on experts' evaluations, we then compared ideas generated in each condition to test our hypotheses.

Analysis and Results

In order to test the effects of task knowledge intensity (H1), an independent-samples t-test was conducted to compare creativity of ideas generated for low knowledge-intensity task (obesity; conditions 1, 3, and 4) with creativity of ideas generated for high knowledge-intensity task (birth mortality; conditions 2, 5, and 6). Table 1 shows a statistically significant difference between the low knowledge-intensity task group ($M=3.40$) and the high knowledge-intensity task group ($M=3.17$; $t(298)=2.12$, $p=0.035$). These results suggest that in general, ideas that address low knowledge-intensity societal challenge task are of higher creativity than ideas that address high knowledge-intensity societal challenge task; participants generate ideas that are more creative when they are more familiar with the topic. Therefore, H1 is supported.

	Topic	**N**	**Mean**	**Std. Deviation**	**Std. Error**
Creativity	Low knowledge intensity	150	3.40	0.78	0.06
	High knowledge intensity	150	3.17	1.08	0.09

Table 1. Group Statistics

In order to test our second hypothesis, the effects of different support architectures on idea creativity (H2), we conducted a one-way analysis of variance (ANOVA). The results suggest that there was a statistically significant difference in idea creativity between groups that used different support architectures ($F(299) = 17.06$, $p<2.2e-16$) (Table 2). More specifically, a Tukey post hoc test (Table 3) revealed that both remixing architecture and stimuli architecture leads to ideas of higher creativity compared to no architecture group. Among different support architecture settings, participants under the remixing architecture generated ideas with the highest creativity. Therefore, H2 is also supported.

	Sum of Squares	**df**	**Mean square**	**F**	**Sig**
Between Groups	27.77	2	13.89	17.06	0.00
Within Groups	241.70	297	0,81		
Total	269.47	299			

Table 2. ANOVA Results - Idea Creativity by Architecture

Conditions		**Mean Difference**	**Std. Error**	**Sig**
No Architecture	External Stimuli	-0.29 *	0.13	0.02
	Remixing	-0.74 *	0.13	0.00
External Stimuli	No Architecture	0.29 *	0.13	0.02
	Remixing	-0.45 *	0.13	0.00
Remixing	No Architecture	0.74 *	0.13	0.00
	External Stimuli	0.45 *	0.13	0.00

Table 3. Tukey Post-hoc Multiple Comparisons

Our last hypothesis proposes that knowledge-intensity of the topic acts as the moderator of the impact of support architectures on the creativity of the crowd-based solutions (H3). In order to test this hypothesis, we conducted a two-way ANOVA. The results suggest that there was not a significant interaction between the effects of topic knowledge intensity and crowdsourcing architecture on the idea creativity ($F(2, 294) = 0.422$; $p= 0.656$). Therefore, H3 is not supported. Table 4 shows the results.

Variable	Sum of Squares	df	Mean square	F	Sig
Intercept	1734	1	1734	2150.80	0.00
Architecture	11.64	2	5.82	7.22	0.00
Knowledge Intensity	4	1	4	4.96	0.03
*Architecture*Knowledge Intensity*	0.68	2	0.34	0.42	0.66
Error	237.02	236	0.81		

Table 4. ANOVA Tests of Between-Subjects Effects

Discussion

Building on the social psychology view of creativity, we first turn to divergent thinking – one of the essential components of creativity – to foster creativity in the setting of crowdsourcing. We identified the positive impact of using crowdsourcing support architectures to trigger divergent thinking and further to increase creativity as opposed to not using any architectures (H2). We differentiated external stimuli from remixing as both can trigger divergent thinking, but to different extents. Our findings along this line in fact contribute to the literature on creativity related to priming, modification, and combination. Our findings are consistent with this literature: External stimuli serve as a priming effect (Lewis et al., 2011) and remixing, on the other hand, serves as modification or combination effects (Nickerson, 2015; Ren et al., 2014).

As another essential component of creativity, we explore different task types that differ in the knowledge intensity. Our findings show that the crowd perform more creatively for the low-knowledge intensity task than the high-knowledge intensity task (H1). These findings have strong implications for the crowdsourcing literature. In prior crowdsourcing literature, scholars assume that the crowd are always able to match their knowledge levels with the posted tasks (Afuah & Tucci, 2012). However, this may not always be accurate. Often, the crowd would rely on external cues to understand the relevance of tasks posted online such as task description (Yang & Bozzon, 2016). However, terminology used in the task description may not translate easily to people from different geographical or cultural backgrounds. In addition, it can be difficult for the crowd to identify a suitable task from the many thousands of available crowdsourcing sites. Thus, our results suggest that crowdsourcing researchers and practitioners need to always filter out crowd members who do not have sufficient knowledge to answer the open call. This would be particularly important for a very specialized tasks such as how to solve the nuclear waste issue. For such tasks, it may be better to turn to professionals and experts who have sufficient domain knowledge for help.

We also argue that the knowledge intensity of tasks can be a moderating role in explaining the impact of the crowdsourcing support architectures on creativity (H3). We argue that even though knowledge and divergent thinking are both important for creativity, there is a hierarchy in their importance. Having sufficient knowledge to understand the context of the task can make one's divergent thinking meaningful and constructive to creativity. By this logic, we expect a significant interaction between knowledge intensity tasks and crowdsourcing support architectures in explaining creativity. However, our results suggest that regardless of the task, the impact of crowdsourcing support architectures on creativity hold the same. This interesting finding in fact may suggest a potential learning effect by these architectures. We conjecture that for the high-knowledge-intensity tasks, the crowdsourcing support architectures expose the crowd to each other's ideas and such interaction can make crowd members learn from each other's knowledge – and collectively they learn to gain the domain knowledge related to the task to the level sufficient to understand the context of the task and to make their divergent thinking meaningful and constructive to creativity. We have seen evidence of learning in a crowd from prior literature (Lasecki et al., 2012). And due to crowd learning, the task type based on knowledge intensity no longer can serve as the moderator. This also suggests in theory potentially if the crowdsourcing requesters can encourage the crowd to learn to the fullest, even if the crowd may not be able to understand a task (such as solving the nuclear waste issue) in the first place, their learning via using crowdsourcing support architectures may allow them to be ready for creativity. This calls for future search to further explore the use of crowdsourcing support architectures that can foster learning as well.

This study has the following limitations. We have asked the crowd to self-report their knowledge level in different topics. While self-reporting is a commonly used technique (Kornish & Ulrich, 2011; Ren et al., 2021), self-reported answers can generate biases such as social desirability bias. In addition, this study used a smaller sample size (n=30 people) for determining high- and low-intensity topics. Since MTurkers are a heterogeneous group with generally different prior knowledge in different areas, future research can increase the sample size. Furthermore, we measured the idea creativity based on novelty and practicality. In the future, scholars can explore other dimensions of idea creativity (Dean et al., 2006).

Planned Future Work

We plan to extend the current study in the following two directions. The first direction is to validate and generalize our findings. We will select additional societal challenge tasks and conduct more experiments to validate our findings in this context. We also plan to collect empirical data from online platforms that incorporate different support architectures to help participants generate creative ideas. For example, Climate CoLab is a platform where the crowd members can be exposed to each other's ideas and modify or combine existing proposals when they create new proposals to address climate issues. This platform embeds both external stimuli and remixing architecture, which allows us to validate our results in real-life settings. We can further explore our conjecture that the crowd's interactions via remixing or getting exposed to each other's ideas may foster learning among crowd members. Lastly, we plan to examine the generalizability of our study by conducting more experiments with other creativity tasks beyond the topic of societal challenge. The second direction is to improve the creativity evaluation. In additional to the human expert evaluation, we plan to adopt objective measurements to evaluate the novelty of the ideas generated such as applying text mining techniques and mapping the ideas on a two-dimensional design space to examine the novelty of each idea. These objective measurements can justify the human evaluation bias and provide us a more comprehensive view on creativity.

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