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ABSTRACT

This paper examines a convergence process of organizing ideas that are generated during collaborative idea generation activities. The method presented reduces the impact of organizing brainstorming ideas on individual participants by dividing the convergence activity into smaller, discrete tasks that can be completed individually, and in parallel, by the participants. The entire pool of brainstorming ideas is subdivided into smaller pools and each participant is then tasked with organizing one of the subsets of ideas. The results show that by dividing up the overall activity into subtasks, the subjects experienced a more favorable environment. Furthermore, the subjects were able to work through their subset of ideas and produce results that were similar to those performing the full sort of the entire pool.

KEYWORDS

Convergence, Ideation, Parallel Sorting, Participant-Driven Group Support Systems

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INTRODUCTION

Advances in technology have yielded a wide variety of communication tools that enable groups to collaborate. These collaborative tools vary in sophistication from very complex to very lean (DeLuca, Gasson, & Kock, 2006). The tools also vary in the types of collaboration that are enabled. Despite the proliferation of tools, many challenges still exist in making collaboration a simple and reliable approach for broad use.

One salient collaboration challenge revolves around the ability of large groups to collaborate (Helquist, Kruse, Meservy, & Deokar, 2011; Kruse, Helquist, & Adkins, 2008; Thorpe & Albrecht, 2004). An increasing amount of research is currently underway on crowdsourcing various tasks and harnessing the wisdom of the crowds. Large groups often do not lend themselves to traditional collaboration tools and methodologies as their characteristics are different.

Two of the key characteristics of large group collaboration are the proximity of the participants and the synchronicity of the collaboration (Helquist, Kruse, & Nunamaker Jr., 2009). Traditional collaboration has focused extensively on synchronous, face-to-face interaction, often led by a facilitator. However, due to physical and logistical constraints, large groups often require the use of physically distributed and asynchronous collaboration (Helquist, Kruse, Deokar, & Meservy, 2013). The increased number of participants, geographic distribution of participants, and asynchronous interaction all increase the complexity of the collaborative engagement (de Vreede, Briggs, van Duin, & Enserink, 2000). These factors can lead to more content and complicate coordination among participants as they cannot easily communicate, focus attention or achieve group understanding as they might in a smaller face-to-face group.

Collaborative work can generally be grouped into two high-level activity types: divergence and convergence. In divergence activities, groups collaborate to brainstorm and generate content. These activities can largely be conducted while the participants work in parallel, each participant being able to submit ideas without direct interaction or coordination with others.

Convergence activities enable the group to synthesize the content by summarizing, combining, and organizing the brainstorming content. The overall effort of these activities is to focus and make the content more valuable or usable by structuring, synthesizing, and prioritizing the content. Typically, convergence activities present an increased challenge to the participants. Because the tasks involved in changing the organization or structure of the brainstorming content are not inherently parallel, there is a need for an increased level of communication and collaboration. Without increased coordination, the actions of the participants will tend to result in task collisions, confusion and wasted effort. Thus, existing convergence activities are also largely serial as the participants are forced to work together as a group, even with a facilitator, to avoid these collisions and reach some form of consensus with regard to the product.

This research investigates convergence activities in an effort to further understand the potential for changing current collaborative processes with respect to large groups. The goal is to improve tools and methodologies that will enable large groups to collaborate effectively and efficiently in a distributed, asynchronous context. This paper is organized as follows. First, literature is presented regarding collaboration and different approaches to conducting collaborative work, followed by research questions, the approach of this research project, and results, applications and conclusion.

LITERATURE REVIEW

Convergence Challenges

Divergence activities have received considerable attention in the literature (Anson, Bostrom, & Wynne, 1995; Briggs, de Vreede, & Nunamaker Jr., 2003; Jay F Nunamaker Jr., Briggs, Mittleman, Vogel, & Balthazard, 1996; Romano Jr., Briggs, Nunamaker Jr., & Mittleman, 1999; Valacich, Dennis, & Nunamaker Jr., 1992). Brainstorming is the activity that dominates the category and it is used extensively across collaboration modalities. It can be performed easily in parallel, by distributed participants, or even asynchronously, as it requires minimal collaborative coordination or interaction between the participants. Although there may be qualitative benefits to working in concert (e.g., the ability to see others' ideas while brainstorming), this is not a requirement. Each individual is able to submit ideas in parallel, yielding a low overhead way to generate content.

In contrast, convergence activities tend to have much higher requirements for use (Briggs et al., 2003). Convergence activities take many forms, but generally, they aim to move the group from having unstructured or semi-structured, and often repetitive, content to having a more coherent, structured, and succinct output of value for a particular end. Unlike the parallel brainstorming tasks, convergence typically requires the group to work serially - considering, synthesizing, aggregating, and prioritizing the content together. These activities require a higher level of collaboration and interaction between the participants, creating an increased level of difficulty and cognitive load.

Work from Chen et al (1996) illustrates that satisfaction levels dip when groups move from divergence (idea generation) activities to convergence (idea organization) activities. Similarly, the amount of time required by the group is greater for convergence activities than divergence activities. The end result is that the groups typically enjoy generating content while coalescing and organizing that content is more time consuming, laborious, and less satisfying.

In contrast to divergence, convergence activities have received little attention in the literature (Briggs et al., 2003). The lack of literature leaves a void regarding a critical component of collaborative work. As a consequence, there exists a need to conduct exploratory research to further understand the complexities of convergence as well as methodologies and tools for mitigating those complexities.

Facilitated Collaboration

Considerable research has been conducted over the years to examine different methodologies to plan and execute collaborative activities. One approach to collaboration is to use a skilled facilitator to lead and guide the group through the various collaborative activities. Research shows the productivity gains that can be achieved by using a skilled facilitator to guide the participants through the collaborative stages (Adkins, Younger, & Schwarz, 2003; Anson et al., 1995; Griffith, Fuller, & Northcraft, 1998; Schwarz, 2002; Zhao, Nunamaker Jr., & Briggs, 2002). As the director of the collaborative group, the facilitator performs a critical role for the group, significantly impacting the productivity and success of the group.

Despite the productivity gains from using a facilitator in collaborative sessions, many organizations have stopped using facilitators. Research by Briggs, et al (2003), investigates the reasons why facilitated collaboration sessions have become less common. Their results indicate that successful facilitators possess unique skillsets and develop organizational knowledge through facilitating various groups. Over time, these facilitators' skills and abilities are recognized and they tend to be moved to other critical non-facilitation duties within the organization.

Even when the facilitator is present, various contextual factors can increase the difficulty of executing the facilitator role. As the size of the group increases, the facilitator must be able to accommodate and direct an increasing number of participants (Helquist, Kruse, & Adkins, 2006b). Additionally, increasing the number of participants tends to increase the volume of content generated by the group. Finally, during the more complicated, and often serial, convergence activities, there are often an increased number of participants that are involved in the decision-making processes. All of these increase the complexity and the load on the facilitator (Helquist, Kruse, & Adkins, 2006a). These factors are further compounded when the participants are geographically distributed and/or working asynchronously. As a result, there is potential to improve the effectiveness and efficiency of collaborative work in these challenging environments through the use of innovative communication tools and facilitation methods.

Collaboration Engineering

Briggs et al (2003) proposed a new collaboration methodology called Collaboration Engineering to enable groups to design collaborative engagements and minimize the need for a skilled facilitator during the actual conduct of the group work. This approach divides the overall collaborative process into separate component activities, called thinkLets, which can be assembled by a facilitation expert into various workflows depending on the context. The idea is that this experienced individual can set the workflow a priori and the semi-skilled participants are then able to follow the collaborative workflow without a facilitator to guide the interaction (Kolfschoten, 2012). This approach to collaboration increases the number of contexts in which collaboration can be successful; however, despite the improvements associated with thinkLets, the challenges of large, distributed, asynchronous groups still remain. Moreover, thinkLets utilize existing collaborative activities and do not address the aforementioned challenges associated with convergence (Helquist, Deokar, Meservy, & Kruse, 2011). Likewise, they do not typically allow for changes in the collaborative script mid-stream.

Participant-Driven Group Support Systems

Participant-driven Group Support Systems (PD-GSS) is a different approach to collaboration that also enables collaboration in contexts without a facilitator (Helquist, Kruse, & Adkins, 2008; Helquist, Kruse, & Nunamaker F., Jr., 2010). PD-GSS utilizes a crowdsourcing methodology to divide up large collaborative tasks into discrete, smaller, and more manageable tasks. Each participant is then able to complete various tasks independently and autonomously. Participants are also regularly asked to evaluate aspects of the product and are then polled to determine where further effort should be applied. The product evolves as the participants evaluate the product, identify opportunities for work, and then perform that work. By breaking up the product into small, discrete tasks and leveraging the participants' individual efforts, PD-GSS enables the entire group to make progress through the collaborative workflow by providing a lattice of structure that would normally be furnished by a facilitator.

This design provides some advantages as compared with traditional, facilitated collaboration as well as the thinkLets approach. First, since participants are working in parallel and anonymously, PD-GSS provides an effective mechanism for working in distributed environments (Helquist, Deokar, et al., 2011). Similarly, the design minimizes dependence on communication and coordination between the participants; the system guides the participants and leverages their judgment in a somewhat dynamic workflow. As a result, PD-GSS also enables asynchronous collaboration. Lastly, the crowdsourcing approach actually benefits from an increasing number of participants. Large groups provide more judgment for evaluating the product, and more resources with which to complete the discrete tasks, expediting the overall collaborative process (Dennis & Valacich, 1993).

Research Objective

The overarching objective of this research project is to explore one of the core activities that is common within convergence, *idea organization*. The goal is to further understand idea organization within the PD-GSS paradigm so that collaboration can be improved with large, asynchronous, and distributed groups.

DISTRIBUTED, PARALLEL SORTING

This research examines the convergence activity of grouping or clustering brainstorming ideas. Typically, this activity immediately follows the divergence stage; the participants identify similar ideas within the brainstorming content and group them. In traditional, facilitated collaboration, this idea organization is performed serially through facilitator-led discussion. It is a time-consuming process that requires the participants to serially consider contributions and come to a certain level of agreement in their organization.

As part of the PD-GSS paradigm, the overall clustering activity can be broken down into smaller tasks. Each participant is assigned a subset of ideas from the overall list of brainstorming ideas. The participant then works autonomously to create clusters from the ideas received. This process is then iterated with other participants receiving other subsets of brainstorming ideas and performing their own clusters. In this fashion, each individual works independently to cluster a subset of the full set of ideas; the individual subset sorts are then combined to form the final sort of all the brainstorming content.

By decomposing the overall sorting process into more manageable tasks, the PD-GSS approach enables each participant to continue their parallel work, avoiding the bottleneck of having to work together converging. These discrete tasks also accommodate participation in distributed and in asynchronous environments. Distributed, parallel sorting aims to address the challenges of convergence and improve end user satisfaction by leveraging the larger number of participants and reducing the burden on each individual participant while removing the requirement of a skilled facilitator.

METHODOLOGY

Research Questions

This research project is exploratory in nature due to the lack of extant literature. As such, two research questions are examined:

1. Does working on a subset of ideas, rather than the full list of ideas, reduce the burden on the participants?

Sorting a subset of ideas, rather than the full list of ideas, may lead to a reduced burden on the participants. Alternatively, sorting a subset of ideas may still lead to a comparable burden.

2. Can sorting a subset of ideas yield a result that is comparable to a full sort?

One of the risks of providing only a subset of ideas to organize is that the participant may not have the entire context from which to organize. Individuals that sort the entire pool of ideas are able to see and process the entire body of information that needs to be categorized, improving the context and vision. It is possible that reducing the contextual awareness of each participant, by limiting the number of ideas to sort, will hinder the overall quality of the final sort.

Experimental Procedure

An experiment was conducted to examine these research questions. Subjects were randomly assigned to one of three treatments, each with varying quantities of ideas to organize. A previous collaborative group generated these ideas. The subjects all used the ThinkTank commercial collaborative software to create the clusters for their subset of ideas. Each subject completed a pretest survey, watched a brief training video on the ThinkTank software and how to use it to complete the sorting task. Additionally, all subjects were given printed instructions that reinforced the video instructions.

After completing the sort in ThinkTank, the subject completed a post-survey to gather various self-report measures before leaving the experiment.

Independent Variable

The independent variable is the number of ideas to be sorted by each subject. Three different treatments were used:

- Condition A required the subject to sort all 110 brainstorming items
- Condition B required the subject to sort 55 randomly-selected brainstorming ideas
- Condition C required the subject to sort either 36 or 37 randomly-selected brainstorming ideas

Dependent Variables

Several self-reported measures were gathered via the post-survey to examine the first research question regarding the burden of participation. These subjective measures included the following:

- Perceived difficulty of the sorting task
- Level of fatigue
- Satisfaction with the process
- Satisfaction with the results

The second research question, the effectiveness or quality of the final sort, was assessed via Normalized Clustering Error (NCE). NCE provides a quantitative metric to compare each subject's sort to a sort generated by an expert facilitator (Roussinov & Chen, 1999). The participant's sort is compared with the expert sort to identify the number of correct associations, as compared with the expert sort, as well as the number of incorrect associations. The NCE value ranges from zero to one. Zero means that the two sorts are identical (a perfect result). One means that there are no similarities between the two (a completely incorrect result).

In this research, the expert facilitator sorted the entire pool of brainstorming idea (110 items) while two of the three treatment groups only sorted a subset of these ideas. In order to run the NCE calculation, the facilitator's sort was pruned to leave only the same brainstorming ideas that the subject sorted. In this fashion, NCE metrics can be derived for all subjects' sorts regardless of the treatment or number of ideas sorted.

In condition A, each subject sorted all 110 items individually. This treatment served as the control group. Since each individual sorted all of the items, each individual completed a full sort and thus their full sort could be compared with the expert sort to generate the NCE value.

Conditions B and C required the subjects to sort a subset of either 55 ideas or 36 or 37 ideas, respectively. These treatments required the pruning of the expert facilitator sort before the NCE calculation could be run.

Participants

All of the subjects were recruited from a Management Information Systems class. In total, 352 subjects participated in the experiment. Condition A consisted of 56 subjects. Condition B consisted of 122 subjects. Condition C consisted of 174 subjects.

RESULTS AND DISCUSSION

Self-Reported Measures

The first set of analyses investigated the impact of dividing up the task on the self-perception measures in the post-survey, including ratings of difficulty, fatigue, and satisfaction.

Difficulty was rated using a seven-point Likert scale from 1, "not at all difficult", to 7, "very difficult". Helmert contrasts were used to investigate the differences between the three treatment conditions. The means and standard deviations are presented in Table 1.

Treatment A, the full 110 item sort, yielded significantly higher difficulty ratings than treatment B, $t(343) = -2.287$, $p = .023$, and treatment C, $t(343) = -2.244$, $p = .025$. No significant difference was observed between treatments B and C. Subjects sorting a subset of the full ideas reported experiencing significantly less difficulty than those completing the full sort.

Fatigue was measured comparing pretest ratings of fatigue with post-test ratings using paired t-tests. Each question utilized a seven-point Likert scale to respond to the phrase, "I am mentally fatigued right now". The response range was from 1, "strongly disagree", to 7, "strongly agree". The means and standard deviations for fatigue from both the pre and post-tests are shown in Table 2.

Treatment A produced a significant increase in the level of fatigue, $t(48) = -5.43$, $p < .001$. No significant differences were found in treatments B and C, as the change from pre to post was only a slight increase. The subjects sorting the entire set of ideas experienced an increased level of fatigue while the subjects sorting a subset of the full set did not.

The first satisfaction measure assessed the subject's satisfaction with the process. This measure utilized a seven-point Likert scale with 1 representing "very dissatisfied" to 7 representing "very satisfied". Helmert contrasts were used to compare the treatments. The means and standard deviations by condition are shown in Table 3.

Treatment A was significantly worse than treatment C, $t(61) = -2.132$, $p = .037$. No significant differences were found between treatments A and B or between treatments B and C. Reducing the number of ideas to be organized to 36 or 37 yielded higher satisfaction with the process ratings than sorting all 110 ideas.

The final self-reported measure examined was satisfaction with the results. This question also used a seven-point Likert scale from 1, "very dissatisfied", to 7, "very satisfied". The means and standard deviations by condition are presented in Table 4.

The Helmert contrasts revealed that treatment A subjects were significantly less satisfied with the results than treatment C subjects, $t(61) = -2.614$, $p = .011$. Treatment A subjects were also significantly less satisfied with the results than treatment B, $t(76) = -2.068$, $p = .042$. No significant difference was found between treatments B and C.

The subset sorting treatments produced significantly higher ratings of satisfaction with the results than the full-sort treatment.

Quantitative Results

The efficacy of each subject's sorting was assessed using the NCE metric. NCE ranges from zero, indicating a perfect match between the expert facilitator's sort and the subject's sort, to one, indicating no matches between the two sorts. Table 5 shows the NCE means and standard deviations by treatment.

A test of homogeneity of variances, Levene's test, indicated that the variances are not homogenous. Accordingly, comparison of the means was examined using the Welch statistic. No significant differences in NCE values were identified between the three treatments, $F(2, 168.2) = 2.644$, $p = .074$. All three treatments produced the same quality sorts as compared with the expert facilitator.

Relationship between Qualitative and Quantitative Results

One additional analysis was conducted to examine the relationship between the self-reported, perceptual measures measuring the burden of the task and objective performance on the sorting task itself. Partial least squares (PLS) was selected as the data analysis technique and WarpPLS was the software used to conduct the analysis (N Kock, 2010, 2011, 2013).

The PLS model was defined to show the self-reported measures loading an exogenous latent variable representing the burden on the participants. This latent variable has a direct link with the endogenous performance latent variable, which is constructed of the quantitative sorting effectiveness metric (NCE).

The indicator loadings and cross-loadings for this analysis are presented in Table 6. These loadings examine the assumption that each indicator variable reflects only one latent construct (N Kock, 2010). All of the indicator variables load properly on their respective latent constructs and are significant.

Table 7 shows the correlation among the latent constructs using the average variance extracted (AVE) to assess discriminant validity. For each latent construct, the square root of the average variance extracted should be higher than any of the other correlations for that latent construct. The data conforms to this standard and the correlation is significant at a $\alpha = 0.05$ significance level.

Figure 1 shows the structural model with the R^2 value for the endogenous latent variable performance as well as the path coefficient. The relationship between the two variables is significant, $p < .01$; an increase in the perceived burden affects a

Table 1. Mean difficulty rating by condition

Treatment	N	Mean	St. Dev.
A	49	3.59	1.74
B	96	2.93	1.60
C	201	3.00	1.66

Table 2. Pre-test and post-test fatigue levels by condition

Treatment		N	Mean	St. Dev.
A	Pre	50	2.96	1.59
	Post	49	3.98	1.68
B	Pre	100	3.05	1.70
	Post	96	3.13	1.58
C	Pre	202	2.84	1.56
	Post	201	2.92	1.56

Table 3. Mean satisfaction with the process by condition

Treatment	N	Mean	St. Dev.
A	49	4.59	1.72
B	96	5.02	1.26
C	201	5.15	1.27

Table 4. Mean satisfaction with the results by condition

Treatment	N	Mean	St. Dev.
A	49	4.51	1.65
B	96	5.06	1.24
C	201	5.16	1.20

Table 5. Mean NCE values by condition

Treatment	N	Mean	St. Dev.
A	55	.742	.08
B	121	.725	.10
C	172	.709	.12

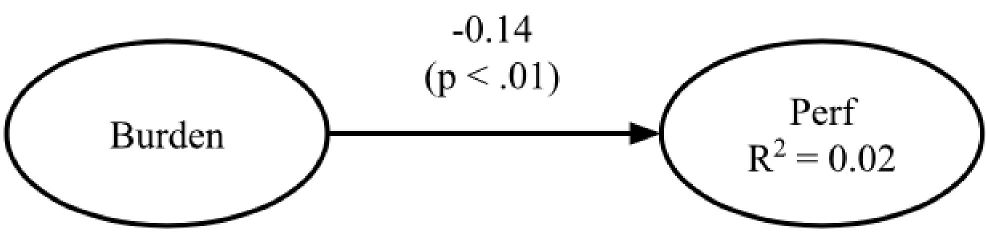
Table 6. Indicator loading and cross-loadings

Indicator	Loading: Burden	Loading: Performance	p-value
Difficulty	0.619	0.026	< 0.001
Fatigue	0.506	0.178	< 0.001
Satisfaction with Results	0.835	-0.070	< 0.001
Satisfaction with Process	0.833	-0.056	< 0.001
NCE	0.000	1.000	< 0.001

Table 7. Correlation among latent constructs

	Burden	Performance
Burden	0.712	-0.123
Performance	-0.123	1.000

Figure 1. PLS Structural model results



decrease in performance effectiveness. However, while significant, this relationship only accounts for 2% of the variation in performance. This low R^2 value is likely due, in part, to the simplistic model and the single exogenous latent variable. Further research in this area is warranted to further analyze a model that captures additional exogenous latent variables and paths.

APPLICATIONS

The ability to break up and perform convergence tasks in a distributed and asynchronous manner opens up many possibilities for practical application. While distributed and asynchronous divergence is straightforward and relatively common, convergence is not. The core activities in convergence revolve around transforming information to make it more useful. Typically, this requires some form of shared understanding among the group members. This research, however, shows that it is possible to successfully divide up and delegate a task that was previously thought to be not easily divisible. Moreover, the participants in this task have been able to successfully create idea clusters and populate them without the benefit of seeing the full range of ideas available. This implies that the participants can, in some cases, successfully contribute in structuring and transforming information into a collaborative product with incomplete information. This provides interesting potential for many purposes.

The driving force behind this research was to identify realistic means for making large-scale PD-GSS a reality. Participants have a limited capacity for attending to the wealth of information developed by large groups. If each participant has limited attention, the collaboration process must present individuals with limited information on issues. Currently, this is not done and users are required to invest a great deal of effort, or those running the process simplify the task. The underlying idea behind PD-GSS is to break up the collaborative task into smaller tasks that can be successfully performed by individuals. In effect, it is trying to perform collaborative work as an aggregation of discrete individual actions. This approach allows practitioners to scale collaborative processes beyond the typical group sizes that are seen today.

Beyond improving the ability to scale and distribute collaboration, this approach may also yield a decrease in the complexity of the processes and associated support. For instance, once convergence tasks can be performed in a more mechanistic and predictable fashion, the dependence on a skilled facilitator for process guidance is decreased. By lowering the costs of collaboration, both financially and in terms of complexity, practitioners and researchers may be able to open up a broader variety of tasks to group-derived solutions. This may also help to minimize the bias and influence of facilitators, which can be introduced through traditional facilitation (Briggs, De Vreede, Nunamaker Jr., & Tobey, 2001).

Additionally, breaking up and distributing convergence tasks may enable collaborators to engage a broader population of participants. Currently, participation in convergence tasks requires a high degree of attention and commitment as participants are asked to look at all of the data and work to develop shared understanding in order to contribute to the transformation of the information. When it is possible to break up this convergence task, it is also possible to get the marginal value of contributions of many less committed people as they can be asked to participate on simpler tasks for shorter durations.

In looking for an illustrative example of where this approach might be beneficial, it is best to select a class of problem that is difficult both in terms of scale and task complexity, and also has limits on the general commitment level of the participants. Often, public policy and planning issues meet all three of these requirements. Regional transportation issues, for example, can be solved in any number of ways and are of interest to the majority of adults in the community. Nevertheless, solution sets are usually developed by small numbers of professionals augmented with highly motivated individuals and special interest groups that will participate in public meetings. Government officials may be able get some broader public input through surveys or interviews, but these typically are of more use in gauging support rather than formulating options. Through a series of divergence and convergence activities, the government officials may be able to take a large group from the initial problem to a recommended solution. This example assumes an on-line web site that can host the collaborative activities.

The first step in this process would be a divergence task to brainstorm ideas for addressing a problem or situation. In this example, the government might post a question to the public such as, “how can the city of Springfield improve rush hour traffic?” The public participants would then openly brainstorm ideas. In the next round of the process, the government could utilize the clustering activity investigated in this effort to organize all of the previously developed ideas. Successive rounds of brainstorming and clustering could also be utilized to flesh out pros, cons, constraints, resources and timing associated with each cluster. Voting can also be integrated into the process at any point to decrease the number of issues or details being considered by the group. Ultimately, with only brainstorming, clustering and voting, a very large group can collaborate to produce a detailed and substantive product that better reflects public sentiment than can typically be achieved today.

The same approach could be utilized in more traditional, face-to-face, collaborative settings. A meeting facilitator would conduct the traditional divergence brainstorming activities as usual. However, instead of working as a full group to organize and transform all of the material from the divergence activities, subsets of smaller groups could work through subsets of the divergence material. By doing so, the group could continue to work in parallel rather than be forced to perform convergence in a serial manner. This could both speed the collaboration process and increase participant satisfaction with the process.

CONCLUSION

The objective of the parallel sort is to divide the convergence activity of idea organization into smaller tasks to reduce the impact on individual collaborative participants. By completing partial sorts rather than full sorts, the subjects experience an easier environment. Additionally, it affords the possibility for asynchronous and distributed participation in sorting tasks, which would allow collaboration with large groups.

Analysis of the self-reported measures provides support for the idea that the partial sort treatments produce a less demanding experience. Subjects reported being less fatigued and found the experiment less difficult. Similarly, partial sorting produced higher levels of satisfaction with the collaborative process as well as the end result. Ideally, the decreased impact from participating in collaboration may lead to improved motivation to participate in collaboration and to stay engaged in the collaboration. Future research is needed to investigate this impact.

The quality of the final sorting was no different between the three treatments. These results lend support for the idea that even though the treatment conditions only sorted a subset of ideas, this limited view of the entire brainstorming pool did not hinder their ability to accurately organize the brainstorming ideas. The implication of this finding is important in the support of the PD-GSS paradigm, as each participant can contribute to the overall group effort while both lowering requirements on each individual and potentially speeding the convergence process.

The next research challenge is to investigate methods to aggregate these partial subsorts into one full sort that constitutes the summation of the group work. In this fashion, individuals can work independently, categorizing subsets of ideas, while the system aggregates these individual subsets into a meaningful whole. Research is currently underway in this area.

While not yet complete, this work is producing promising results that are interesting to both researchers and practitioners. As mentioned previously, for researchers, this is an entirely new area that needs to be explored. The notion of dividing up tasks and recompiling the final sorts in a PD-GSS fashion aligns closely with many of the same themes and goals of crowd sourcing, which is becoming a large area of research. Many questions exist as to the specifics of executing a PD-GSS collaborative process that enables the proper decomposition of large tasks into smaller, discrete tasks.

From a practitioner perspective, these results provide interesting application into new methods for executing convergence activities. One such approach is that a facilitator may choose to decompose one larger collaborative group into smaller collaborative group, each smaller group working on a sub set of the problem concurrently. The implication from this approach is that not only does it reduce the burden on each participant but it also reduces the time to achieve a first draft of an organized set of ideas. This approach may yield participants that are more eager to stay engaged and participate in the collaborative activities due to the decreased burden. It may also open up participation to those with less time or commitment than is typical today. The most important implication may be that people can begin to perform higher value collaborative work with less process management. By lowering the barriers to collaborative work, practitioners can open up a broader variety of problem sets to collaborative solutions.

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