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DESIGN CONCEPT STRUCTURES IN MASSIVE GROUP IDEATION

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ABSTRACT
Empirical work in design science has highlighted that the process of ideation can significantly affect design outcome. Exploring the design space through both breadth and depth increases the likelihood of better design outcomes. Furthermore, iteratively attempting to solve challenging design problems in large groups over a short time period may be more effective than protracted exploration by an isolated set of individuals. There remains a substantial opportunity to explore the structure of various design concept sets. In addition, many empirical studies cap analysis at sample sizes of less than one hundred individuals. This has provided substantial, though partial, models of the ideation space. This work explores one new territory in large scale ideation. Several conditions are evaluated. In the first condition, an ideation session was run with 2400 individuals who operate in a communal design organization. They were inside a single room, in groups of five to six individuals. In the second condition 1000 individuals ideate on the same problem in a completely distributed environment and without awareness of each other. We compare properties of solution sets produced by each of these groups and activities. To achieve this goal, analytical tools from network modeling theory are applied as well as traditional metrics such as concept binning with saturation analysis. Structural network modeling is applied to evaluate the interconnectivity of design concepts. This is a strictly quantitative, and at the same time graphically expressive, means to evaluate the diversity of a design solution set. Observations indicate that the group condition approached saturation of distinct categories more rapidly than the individual, distributed condition. The total number of solution categories developed in the group condition was also higher. Additionally, individuals generally provided concepts across a greater number of solution categories in the group condition. Individuals in the distributed condition generally provided solutions at a greater depth or level of variance within categories. Statistical measures included: Student's T-test for the bin differentiation; path length analysis, and modularity clustering in the network assessment. These results concur to validate the observations. The indication for design practice is that groups of just under forty individuals would provide category saturation within group ideation for a system level design, while distributed individuals may provide additional concept differentiation. This evidence can support development of more systematic ideation strategies. Furthermore, we provide a method for automated evaluation of design solution sets using networking analysis techniques. These methods can be used in complex or wicked problems, and system development where the design space is vast.

INTRODUCTION
Combating Ideation Rate Decay
There is a generally open problem in design science to map the characteristics of ideation. A working model of ideation can lead to better design processes and perhaps even deeper understanding of human cognitive models. Empirical research suggests that idea generation rates (for the individual) decrease asymptotically or logarithmically over time [1]. Again, another studies shows that the number of categories explored also decreases steadily over time throughout an ideation session [2]. The typical designer becomes exhausted after an ideation period of roughly 50 minutes [1].

However, complex multivariate design problems have correspondingly large design spaces to be explored. Designers must engage in alternative approaches to manage the prospect of exploring large design spaces, as brute force exploration by an individual is unlikely to succeed. One approach to resolve this limitation is to engage multiple designers. Naturally the following research questions arise:

1. How many designers are required to tackle design concept solution ideation for complex problems?
2. In what manner should ideation be conducted with these designers?
3. What tools can be used to evaluate resulting large ideation sets?

Crowdsourcing Solutions to Wicked Problems

A common human activity is large group decision making. Typically groups are involved in the solution of complex and wicked problems. Roads are an example solution to the complex problem of transportation. In such scenarios, a large number of stakeholders are involved. Therefore a large number of stakeholders should also participate in the design [3].

Crowdsourcing has been defined as the act of transferring a function from an individual or small group to a large network via an open call [4]. Crowdsourcing is often executed through a digital platform. One typical, current, use of crowdsourcing in design is for the purpose of evaluation. A consensus model is typically used in such cases [5]. Extraction of expert-level ratings have been achieved through application of a quantitative consensus model to identify clearly indicated assignments. Essentially, ratings are taken not based on an average but on high modality or ratings for which many raters agree [6]. Voting systems are a historical instance of this archetype.

Generation of meaningful results through crowdsourcing has been demonstrated in a number of studies. For example, Schaffhausen et. al use the crowd to identify need statments for a product. The number of useful need statements was proportional to the number of users queried). This is a positive result as other empirical studies have correlated need statement quantity to design quality [7].

This paper will explore the use of crowdsourcing for ideation. Crowds typically provide colloquial expression of design concepts. Therefore basic lemmatization and trimming of non-descriptive parts of speech, e.g. "a" or "could" are typically applied to raw results. This results in a set of semantic concept tokens which facilitate subsequent analysis, e.g. "railway" or "hub" [8].

Managing Team Ideation

Another dimension of considerable interest in strategic design is in the usage of teams. One study has shown that designer's mental models are receptive to team exposure and that just seven minutes of team interaction significantly increased the similarity of individuals design strategy; conversely working alone was show to decrease the similarity of the self-reported design plan [9]. At the same time, other researchers show that the originality and innovativeness of initial concepts is improved by group members [10]. Design solutions come from individuals. The role of the group is to provide a motivational structure [11].

Taylor et al. have proposed several mechanisms that may inhibit group ideation. These are *production blocking, evaluation apprehension,* and *free riding* [12]. C-Sketch is a hybrid ideation technique which has been proposed to prevent some of these known limitations in group ideation. Individuals ideate in a group, but working on their own sheet of paper. They then share these ideas for comment by each other member in successive rounds [13]. C-Sketch was used in this study.

These observations lead to questions about distributed groups. Researchers have demonstrated that electronic ideation tools may increase the capacity to work in parallel [14]. Other studies have demonstrated successful team collaboration projects through virtual interaction environments [15]. However, there may be tradeoffs in the performance between collocated and distributed teams [16].

Analyzing Large Data Sets

Data sets produced by such distributed or group ideation efforts may become cumbersome to analyze. A necessary question follows, 'How does a human intelligence organize data [17]?' An answer to this question provides a framework on which to build an automated yet comprehensive analysis that can interpret large data sets. One hypothesis is that ideas emerge naturally from a dynamic interactions within a multi-level, modular semantic space [18]. Therefore intelligent analysis tools often begin with semantic analysis of a data set. The first step in data analysis typically involves parsing, reduction, and lemmatization of a text to isolate the functional terms only [19]. Text mining is applied to then cluster ideas based on meaningful metrics such as cosine similarity or other basic weighted vector terms [20]. This approach may be used to build networks of design databases such as the patent database, e.g. to search for functionally similar patents [21]. A research study in design has demonstrated that expression of abstract concepts in semantic terms, rather than an image or sketch, does not adversely affect interpretation of the design concept [22]. Fu et. al have employed Kemp and Tenenbaum's Bayesian model for discovering structural form [23]; and applied this to identifying well-fit structural forms in the patent database. This approach enabled the researchers to evaluate analogical distance of the designs (patents) [24].

EXPERIMENTAL APPROACH

The evaluate the research questions, an experiment was developed with two conditions. In the first condition 2400 individuals tackle a common design problem "Design the next generation of public transportation." In this study, fixation effects were mitigated through the use of a functional problem description as suggested by [25]. These individuals are engineers and designers with a broad range of experience (approximately 10-12 years of industrial experience on average). In this condition, individuals were clustered in groups of 5-6 individuals seated at a round table. Participants were asked to ideate on the selected problem. Solution sheets were collected at the end of the round. The initial ideation pass lasted approximately 20 minutes. Of these individuals, the solution set was down selected to 1000 individuals for this analysis. A simple overview of the research methodology can be found in Figure 1.

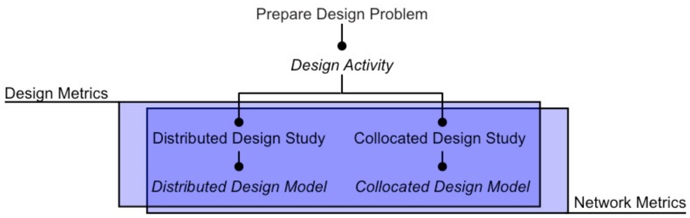

Figure 1: Wireframe overview of experimental approach

In the second stage we use an online crowdsourcing tool to conduct another series of ideation exercises. These participants explored the same design problem. We apply the method proposed by Wu to implement a generative crowdsourcing exercise.

1. Select a platform (in this case Amazon's Mturk) [4].

2. Conduct pilot trials of the design exercise

3. Progressively scale the task

In the second ideation session, users are restricted to ideate through text input only. While in the first set users heavily favored text, they were also able to submit sketches as they were using a sheet of paper. However, Linsey et. al found that a words only condition no statistically significant differences in terms of quantity or variety to a words with sketches condition. These differences are not statistically significant [26]. After the studies were conducted, a set of analyses were applied to the resulting data.

METRICS AND DATA ENCODING

Variety

One measure of a design solution set is *Variety.* It is a measure of the explored solution space within an ideation activity. A set of similar ideas should return a low variety as only a portion of the design space was explored [27]. A variety assessment applies to an entire set of ideas. The analysis evaluates how different two or more ideas are from each other [28]. In this paper we apply a standard binning strategy based on high level categories or solution avenues and individual or unique solution bins. Design solutions which are evaluated by the raters to be effectively the same are grouped in a unique solution bin. Shah's original metric involves assignment of a degree of difference within branches of a solution tree. The number of ideas in each tree is tabulated [29]. In this case the depth of the tree is two and therefore a simplified variety metric is provided in terms of the coded frequency distribution of unique solutions in the first and second tree level between the two conditions. Research has supported that the encoding phase is the most critical [30].

Inter-rater testing is applied to support this characterization. Inter-rater agreement functions to support the alignment of a rating system [31]. In this case, a consensus method was applied. In a typical approach, solution types for unique solutions is generated bottom up, while a running list of categories is built up progressively [32].

Saturation

Saturation analysis is also applied. In saturation testing, the number of unique solutions is counted as each new participant is evaluated. The expected form of a saturation curve is pseudo-logarithmic. A saturation plot, by definition, will reach a point at which there is no significant increase in the return of new solutions by evaluating a new participant [33]. It is a robust empirical test to determine whether a sufficiently large sample set has been taken. By contrast sample size calculation is an a-priori *predictor* of sample sizing while saturation is a posteriori *validator* of sample size.

Network Diameter a.k.a. path length

Network Diameter measures the maximal distance between all pairs of nodes. In a network, the distance d_{ij} between two nodes, labeled i and j respectively, is defined as the number of edges along the shortest path connecting them.

Betweenness Centrality measures how often a node appears on shortest paths between nodes in the network. It is determined by solving one single-source shortest-path problem for each node. At the end of each iteration, the dependencies of the source on each other nodes are added to the centrality score of that node. Nodes with high betweenness centrality often appear at center or boundary of a cluster [34].

Modularity Test

Modularity measures how well a network decomposes into modular communities. The modularity test uses a method to extract the cluster structure of large networks. Cluster detection requires the partition of a network into cluster of densely connected nodes, with the nodes belonging to different clusters being only sparsely connected. In our case modularity helps identify major clusters of solution categories. Many networks have a *community* structure, where nodes are linked in dense connected groups [35-37].

RESULTS

Saturation within conditions

A random selection of individuals was made sequentially to form the nominal groups. We define a saturation point as the first participant in a series of at least 15 individuals added wherein no new category is found. Saturation is also validated through logarithmic curve regression to identify

Unique categories, within the distributed condition, appear to saturate more slowly with a higher total number of unique categories, flat line observed after nominal group size of 114 individuals. The total number of unique categories identified was 16.

Unique categories, without the group condition, with saturation reached after a nominal group size of 38 individuals. The total number of unique categories identified was 22. See Figure 2.

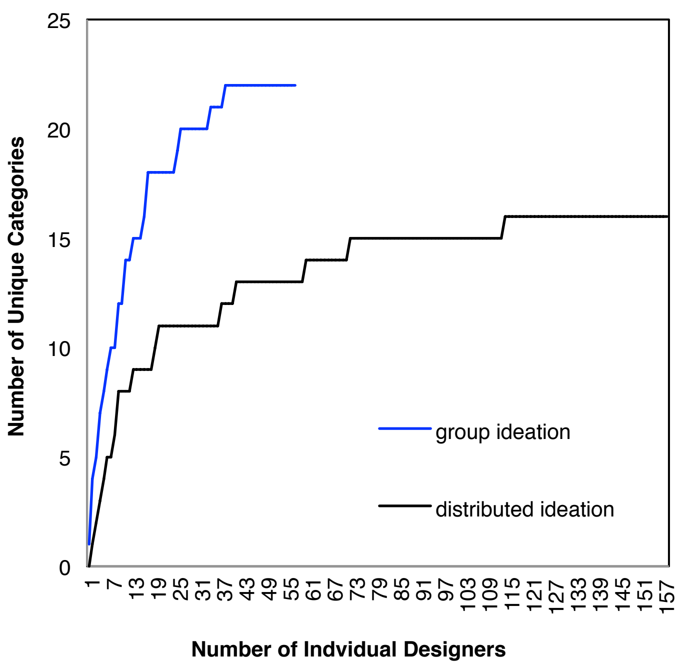

Figure 2: Saturation of group and distributed ideation conditions. Notice that the group ideation reaches a higher number of categories and with fewer individuals.

Solution Categories explored by Each Individual
We evaluated the distribution of unique categories generated by each participant within the two conditions. This is performed at the categorization level. We provide a complete frequency distribution for a random sampling of 50 participants. This provides a baseline confidence level of 95% with better than a 0.15 confidence interval as a preliminary evaluation.

Individuals in the distributed ideation session explored fewer categories on average. Individuals in the group ideation session explored more categories on average as compared to the distributed group. The difference in this distribution is significant with Students T-test at $p < 0.001$. See Figure 3.

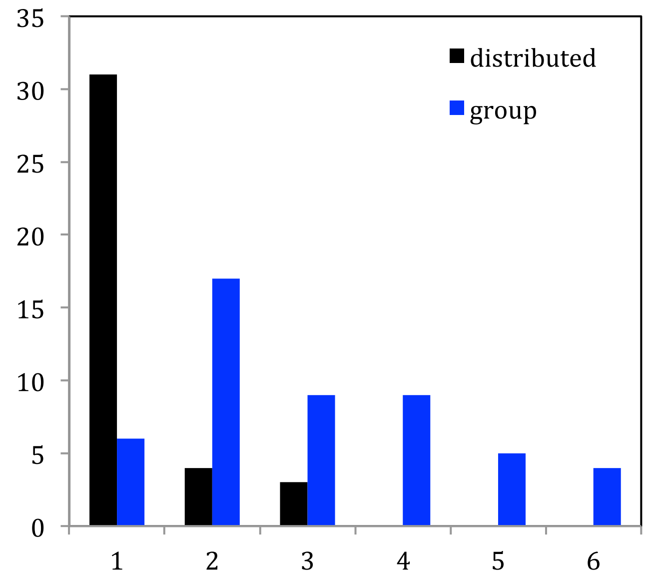

Figure 3: Number of solution categories explored by each individual, histogram.

Unique Solutions per Solution category
We also evaluate the frequency distribution of the number of unique solutions in each category. This provides an estimation of variety at the second hierarchical level. Although this is generally considered a weaker term of variety, it is interesting to note that there is a roughly equivalent frequency distribution of unique solutions in a bin across the two conditions, there was a statistically significant higher number of unique concepts in the group condition. Indicating that the group condition follows selector type ideation while distributed teams tend towards explorer type ideation [38]. See Figure 4. We provide a complete frequency distribution for a random sampling of 50 solutions. This provides a baseline confidence level of 95% with better than a 0.15 confidence interval as a preliminary evaluation.

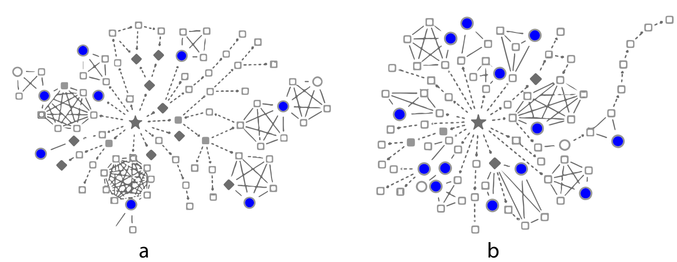

Figure 4: adapted from Kim [38] (a) selectors display more distributed designs; (b) explorers look evenly across many designs but within a close proximity

This indicates that while the Turks are exploring a more concentrated set of ideas, they explore slightly fewer within those concepts particularly with regards to high level categories. The difference in this distribution is significant with Students T-test at $p < 0.001$. See Figure 5.

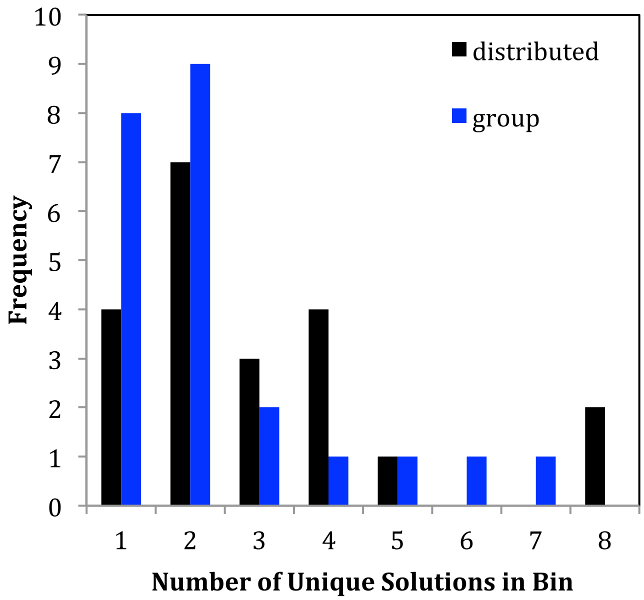

Figure 5: Number of unique solutions in bin, histogram.

Graph Structure Sample

A small sample is taken from each data set to visually demonstrate the graphical characteristics (using Gephi v8.5.2). This visualization is based on a sample set of ten individuals from each condition. In general. this means that each participants shares many nodes with their neighbors. A link occurs when two individuals shared and idea with a common feature.

Notice that there are relatively fewer nodes in the group ideation condition. They do have more distinctly separate clusters. Essentially, fewer unique function/feature nodes have been identified yet there are a larger number of separated concept communities. There is more breadth across high level categories. This form matches the selector type of ideation pattern as proposed by Kim [38]. See Figure 6.

There is a relatively large number of nodes connected to each cluster. All of the clusters, even in this small graph are connected. This is representative of the individual ideation condition. There were more distinct function/feature nodes within individual community clusters. However there were fewer clusters overall, and these clusters are closer to each other. This form matches the explorer type of ideation pattern as proposed by [38]. See Figure 7.

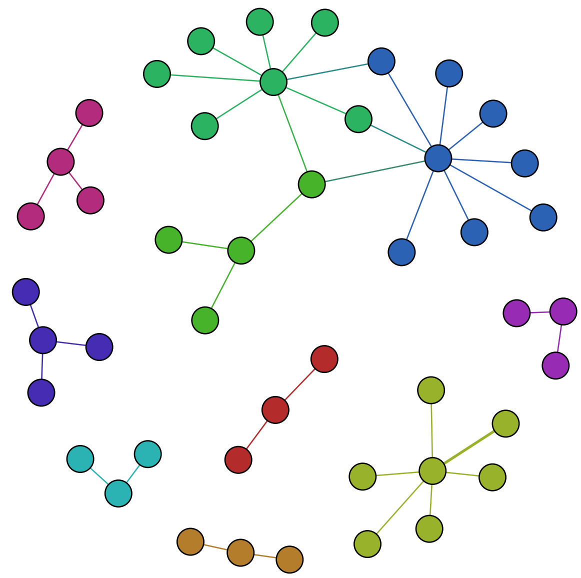

Figure 6: Sample network diagram of group condition, n = 10. Notice the wide spread of unique, unconnected solution communities; representative of higher variety; selector archetype.

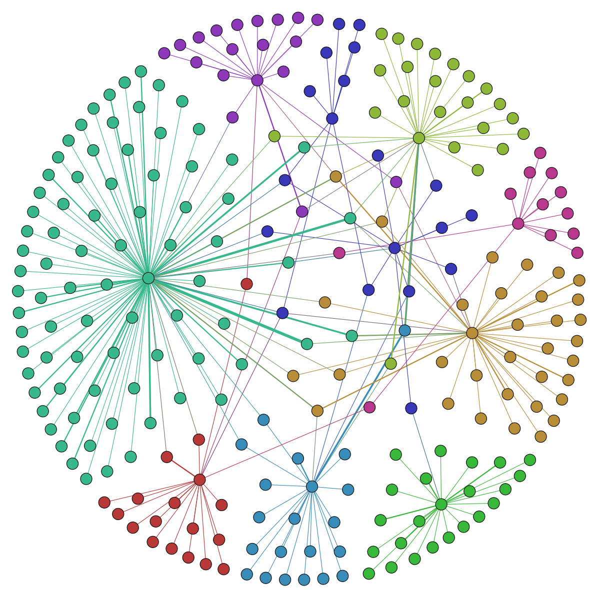

Figure 7: Sample network diagram of distributed ideation condition, n = 10. Notice that the ideas are clustered into a more tightly packed community; indicative of lower variety; explorer archetype.

Statistical Analysis of Graph Structure

The following statistical analyses are applied to validate the observed qualitative properties of the graphs and data. This analysis was algorithmically applied to the entire data set consisting of all the designs produced by 1000 individuals in each condition. The total number of unique participants whose results are reported in this section is 2000. This provides an opportunity to explore fully developed normal distributions within the results.

Table 1: Statistical network analysis results

	distributed	group
Average Path length	3.92	4.14
Number of Communities	22	32

Additionally we explore the closeness distribution across all nodes.

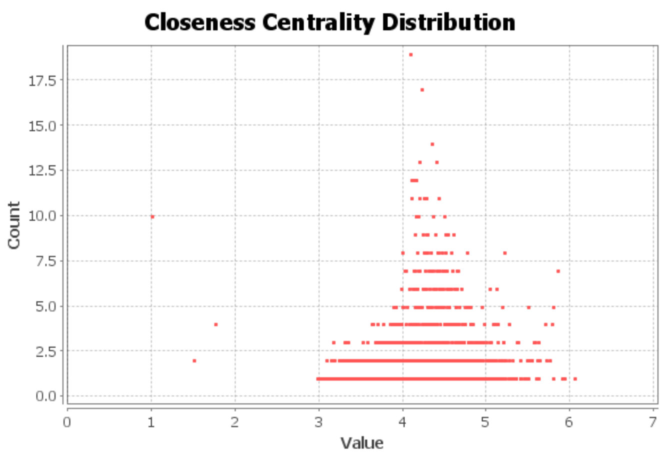

Figure 8: Closeness centrality distribution within the group ideation condition. Notice that the ideas are more well distributed as the average path length is 4.14 nodes.

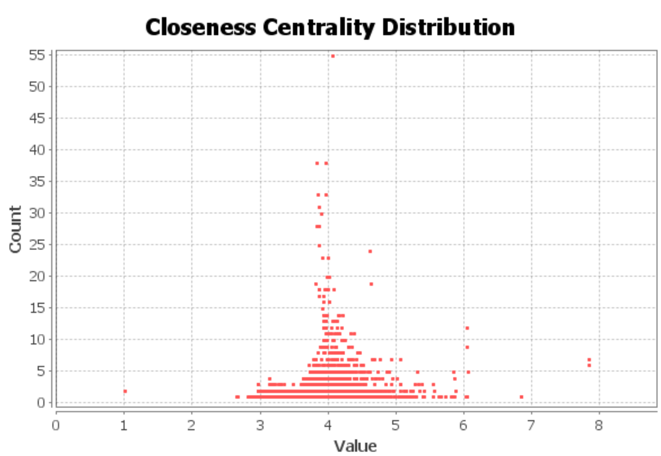

Figure 9: Closeness centrality distribution within the distributed ideation condition. Notice that the ideas are more tightly packed as the average path length is 3.92 nodes. P < 0.001 that this is a smaller mean path length using Student's T-test.

DISCUSSION AND CONCLUSION

This research has analyzed the ideation results of 2000 participants across a co-located group and distributed nominal group conditions. The results were analyzed with traditional design metrics as well as a networking approach.

It was observed that the collocated group ideation condition outperformed the distributed condition with respect to the total number of unique solution categories resolved, the saturation rate, and the number of categories found by each participant on average. There were more unique solutions in each category for the distributed group.

It is difficult to explain why concepts in the group condition exhibited less variety of unique solutions. Previous empirical research in psychology has shown that short term memory has a spatial component [39]. This may be a contributing factor to the tight clustering observed in the unique solutions of the group ideation condition. Essentially, participants in the group condition may be more familiar with a particular common instance of a solution or inspiration. While in the distributed condition, participants from around the world would encounter variants of products and systems used in analogical reasoning. Working memory plays a significant role in the creative processes, therefore high order cognitive modeling is essential for future research in design [40].

Networking analysis validates the findings of human rated binning. Furthermore, a visual representation of the two solution spaces is provided. It can clearly be seen in Figures 6-7 that the group session has a larger number of independent nodes (more distant solutions) while in the distributed solution session there are a large number of closely linked (more similar) unique solutions.

Finally, statistical network analysis was applied on the entire data set to validate that larger number of concept communities (roughly comparable to solution categories) identified in the group condition was higher than in the distributed condition. Furthermore closeness centrality distribution shows that the average node to node distance was larger in the group condition (i.e. the ideas were less-like each other).

The value of mixed ideation, with individuals ideating in a group has been demonstrated for the generation of high level concepts. In tandem, it is also possible to leverage distributed or crowd sourced design to in cases where it may not be possible to assemble a group of designers.

We identify for the first time that group ideation leads to concept saturation more quickly and a larger total number of unique design concept categories. Therefore group ideation has value to explore the breadth of the design space.

Distributed design leads to a higher number of individual solution categories per category and thus may be a valuable to mine a particular solution category in greater detail. In other words distributed ideation has an advantage in exploring the depth of a design space. This may be of some concern from a network modeling perspective. If the core becomes too heavily clustered or loses efficiency a cascade failure may occur [41]. Or, in the context of design, if the ideation is too heavily clustered around a core solution category, and that category fails (is not a good design) then the project is at risk. Therefore it may be critical to employ a mixed approach of group and distributed design to attain a broad and deep exploration of the designs space. Network analysis, as shown in Figures 6-9 also provides a novel avenue for quantitative design concept binning.

Areas for future improvement or research include evaluation of an additional condition, consisting of a compact and experienced design team. Evaluation of modification rounds in ideation, where original ideas are modified. The objective of this last condition is to evaluate the mutation characteristics of ideas within the provided conditions. These further studies will help to expand the results reported in this paper.

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