Using Adaption-Innovation Theory to Simulate Robustness in Design Teams

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Abstract
Creative design is often accomplished through teams, and the specific composition of those teams can limit or enhance the sum creativity. However, it is not known how team composition is related to a team's ability to achieve good solutions over various problems (i.e., robustness). Here, we build that relationship between composition and robustness through a series of agent-based simulations. The factor that we specifically investigate is cognitive style, which describes the manner in which individuals solve problems and present solutions in social interactions based on cognitive processes. Under Kirton's Adaption Innovation (KAI) Theory, cognitive style is related to creativity. Specifically, an individual's KAI score, the defining measure of cognitive style, describes the degree to which they prefer high-utility solutions, or high-novelty solutions – the two necessary conditions for creativity. In many cases the long-term success of a team is closely tied to their ability to perform consistently well across multiple design problems, termed robustness. Leveraging computational agents, we use adaption-innovation theory as the primary factor to examine robustness among homogenous and heterogeneous agents. Different approaches to composing teams with homogenous and heterogeneous cognitive styles did not substantially impact robustness. However, the average robustness of the teams improved as team size increased.

Introduction

For teams to be effective, we expect members to be able to collaborate with each other in sharing ideas and offering support to achieve their goals. However, as teams are often composed of individuals from diverse backgrounds and skill sets, issues may arise that create differences and conflict within the team. While the divergence of opinions can simulate creative ideas and solutions (Chen, 2006), it can also be detrimental to the design process, and be a strong negative correlator to team performance in highly complex tasks (De Dreu & Weingart, 2003). A team that can work cohesively and consistently across complex tasks and unstable environments are considered to be *robust*. Robustness is often used interchangeably with flexibility, describing the ability to respond effectively to changing circumstances (Saleh, Mark, & Jordan, 2009). Robust teams require creative solutions to reduce individual inconsistencies among members and accomplish goals. Designing a team that not only performs well, but is robust to deviations in individual member's behaviors is optimal, as the makeup of the team and team members is often subject to change over time (Wiegand & Potter, 2006).

The computational methods used enable the opportunity for larger scale team studies and mitigates the issues that arise when studying teams using traditional methodologies (Lapp, Jablokow, & McComb, 2019b). Multi- agent systems modeling can be used to design optimal team formation for achieving a given set of tasks, as it becomes possible to compare different team compositions and structures (Crowder, Robinson, Hughes, & Sim, 2012).

In this paper, the objective is to achieve robustness through team composition. This is specifically accomplished by focusing on cognitive style and its role in problem solving and creativity. Cognitive style refers to the preferred way an individual processes and organizes information (Messick, 1976), influencing the decision making and problem solving processes (Urban, Weaver, Bowers, & Rhodenizer, 1996). Kirton's Adaption-Innovation (KAI) theory refers to cognitive style in which the manner of accomplishing cognitive tasks can be placed on a continuum (Jablokow, 2000), with the extremely "adaptive" and extremely "innovative" thinker are on either end of the spectrum (Bobic, Davis, & Cunningham, 1999; Kirton & De Ciantis, 1986). Specifically, an adaptive thinker prefers more structure and group consensus to achieve improved solutions, sticking close to the "status quo" and making incremental changes (Samuel & Jablokow, 2011). In contrast, an "innovative" thinker feels constrained by rules, cutting across paradigms and the existing structure to solve problems "differently", with less concern for group consensus (Samuel & Jablokow, 2011). While team performance can be attributed to a number of factors, the examination of cognitive style offers one avenue that is particularly relevant for creativity in design.

In order to study the composition of human teams with varying cognitive styles, we use the Python implementation of the KAI Agent-Based Organizational Optimization Model (KABOOM) (Lapp et al., 2019b) to generate and investigate teams of computational agents with varying simulated styles. The KABOOM framework enables investigations of the impact of KAI Theory on teamwork. In this framework, autonomous agents with various cognitive styles interact to solve a diverse set of problems and maximize the objective function, indicating performance (Lapp et al., 2019b). KAI is measured, in both humans and agents, with three subscores for Sufficiency of Originality, Efficiency, and Rule Group Conformity, which are the determinants of cognitive style (Lapp et al., 2019b). Sufficiency of originality is of particular importance, as it defines the degree to which individuals prefer high-utility solutions, or high-novelty solutions – the two necessary conditions for creativity.

We evaluate the performance of homogenous agent- based teams (in which each member of the team has the same total KAI score) and modify team composition to form various heterogeneous agent-based teams to identify the best combination of KAI scores to maximize robustness. Specifically, this research seeks to answer the following questions: (1) In homogenous teams where each agent has the same KAI score, which cognitive style is the most robust? (2) Which heterogeneous team composition provides the best robustness? (3) How does the size of the team affect its robustness?

Methodology

In KABOOM, the goal of the agents is to maximize their objective function using a simulated annealing optimization algorithm in which the agents explore widespread solutions from a highly stochastic approach gradually changing to a more downhill search. This reflects the nature of human problem solving (Cagan & Kotovsky, 1997). In KABOOM, heterogeneous agents possess unique cognitive styles that modify their exploration of the solution space.

In this paper, a solution is a set of parameters that define a position in the solution space, and the quality of a solution is the value of the objective function for those parameters. Team performance is taken to be the best solution any individual on a team has found.

The Problem Set

This paper implements an abstract mathematical objective function, or design problem, that can be tuned and scaled in predictable ways. It is represented by a scalar objective function f(x) of *n* dimensions (variables). The objective function used is a summation of a quadratic function and a sinusoidal function in the form:

$$f(\vec{x}) = \sum_{i=1}^{n} \alpha \cos\left(\frac{\omega \vec{x}_i}{\beta}\right) - C\left(\frac{\vec{x}_i}{\beta}\right)^2 \quad \text{for} -0.5 \leq \text{xi} \leq 0.5$$

This function is varied in two ways: (1) by scaling the independent variables in all dimensions using the scaling parameter, β, and (2) by scaling the oscillation amplitude of the sinusoid, α. The first parameter affects the size of the search space, while the second parameter affects the amplitude of the sinusoid. By varying these parameters, we create 25 unique design problems for running our simulations that may favor different cognitive styles.

According to past research from Lapp et al. (2019), adaptive agents (those with lower KAI scores) are hypothesized to best solve problems with a high oscillation amplitude and smaller search space. Innovate agents (those with higher KAI scores) are therefore more suited to solve problems with a smaller amplitude and a broader search space. By assessing the performance of a team with a specific composition across each of these problems, it becomes possible to assess robustness.

Team Composition Strategies

To evaluate the effects of team composition on robustness, we formed teams using three composition strategies. In the first, referred to as organic composition, teams were generated by selecting individuals with KAI scores corresponding to the distribution of scores observed in the general population (mean=92.93, std=18.20). Second, homogenous teams were each comprised of agents with the same KAI score. The seven KAI scores were linearly spaced from 60 to 140. Third, heterogeneous teams were produced by sampling from the uniform distribution of the complete range of scores. This selection was iteratively narrowed to more mid-range scores to produce a variety of team compositions.

Quantifying Robustness

At the end of each simulation trial, the team's performance is the solution quality of the best solution any agent has had at any time during the simulation, quantified as a numerical value. We examine three values computed from the solution vector. These include the median value of each team, the lower quartile or 25th percentile performance, and the worst score to determine the lower bound on the team's performance. The team's "worst" score does not include outliers.

As the teams are solving a minimization function, lower values indicate a better performance. Thus, higher values indicate a worse score.

Results

Figure 1 displays the results of homogenous team simulation for six agents per team. Results from the simulation with both two and ten agents per team yield similar results.

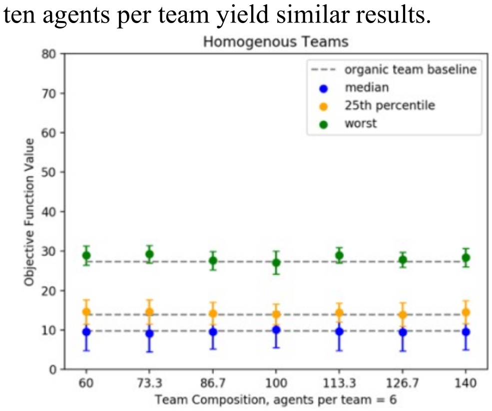

Figure 1. Homogenous team performances with 6 agents per team. Lower values indicate better performance. Error Bars represent absolute deviation. Dashed lines represent average values achieved by organic teams.

These results indicate that among each of the teams, performance remained the same, and we see no clear "superior" KAI score. There were only minor differences between the team's performances.

Therefore, it is not clear whether there is a KAI score that is the most robust and resilient for team composition, as there is very little difference in aggregate robustness. Among the range of KAI scores from 60 to 140, no team significantly outperformed another. Additionally, the median and 25th percentile scores followed closely to the baseline of the normal distribution, indicating that forming teams with homogenous agents yields similar outcomes to organic teams. This aligns with earlier work on cognitive style, in which it has been indicated that different cognitive styles are not necessarily better than one another, simply different (Hammerschmidt, 1996; Jablokow, 2000; Lapp, Jablokow, & McComb, 2019a; Lapp et al., 2019b). Additionally, while the overall KAI score was the same for each member of the team, subscores varied. Two agents with the same KAI values may have slightly different SO scores, affecting their creativity and preferred problem-solving approach. While team performance did not have a significant effect between teams, each of the scores improved as the team sizes increased from two to ten agents per team.

Figure 2 indicates the results of heterogeneous team simulation for six agents per team. Results from the simulation with both two and ten agents per team yield similar results.

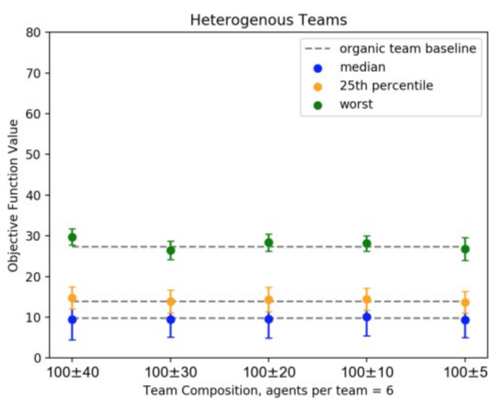

Figure 2. Heterogeneous team performances with 6 agents per team. Lower values indicate better performance. Error bars represent absolute deviation. Dashed lines represent average values achieved by organic teams.

Unlike the homogenous teams, our heterogeneous teams performed slightly better than the organic teams. This may be an indication that utilizing the full distribution of scores may be advantageous, as some design problems may favor the highly adaptive or highly innovative individuals, producing better scores. There might also be some advantages to using a uniform distribution as opposed to a normal distribution for team selection, as uniform distribution allows an equal opportunity for any score to be selected. However, once again, there is not any significant differentiation in performance according to team composition, further supporting claims by Lapp et al. (2019b).

Kirton also claims that a cognitive gap, or the difference in cognitive style between individuals will have a "just noticeable difference" at 10 points, and gaps of 20 points or more will lead to significant problems between teammates (Jablokow & Booth, 2006). Thus, while both the 100 ± 5 and 100 ± 10 team are heterogeneous in that they are comprised of members with different KAI scores, there may not be enough variation in cognitive style to present them as purely heterogeneous.

To investigate how the size of the team may impact its performance, we performed the simulation to study the robustness from two-agent teams to 20 agents per team. The graphical representation of these scores can be found in figure 3.

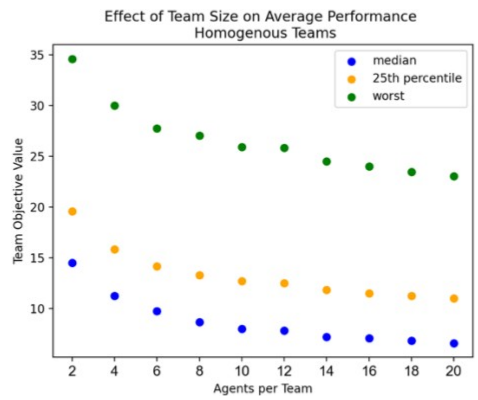

Figure 3. Average performance of the teams for the median, 25th percentile and worst scores for homogenous teams.

We now observe that better scores are positively correlated to larger teams for homogenous teams. However, it should be noted that this result depends on the ability of large teams to function cohesively without hierarchy (which can be a barrier to performance). In practice, teams often form implicit hierarchical structures when larger than six members (Maier, DeFranco, & Mccomb, 2019). The effect of team size on heterogenous teams yielded a similar output. We can also determine that mid-size teams may be more robust than smaller ones, but increasing team size beyond these values may not continue to yield significantly better performances. These findings are commensurate with prior research results on team size and performance, where individuals in teams collaborated with more increasing team size, resulting in larger teams outperforming smaller ones (Mao, Mason, Suri, & Watts, 2016). In theory, larger teams allow for more diversity and opportunities to communicate with and learn from others, accelerating the process of converging to a solution (Marschak & Radner, 1972).

Conclusion

Teams that are able to perform consistently well across various problems are considered robust. The quality of robustness is vital, as it enables teams to be successful and work collaboratively to achieve their goals. There exist prior models of computational creativity that have assessed the way in which existing knowledge is combined to achieve novel solutions (Guzdial, Liao, Shah, & Riedl, 2018). In this research, we utilized the KABOOM model to investigate how creativity can affect a team's overall robustness, by tuning the composition of the team based on KAI value and evaluating performance based on 25 individual problems.

The KABOOM model focuses specifically on cognitive style and does not create a comprehensive representation of team problem solving, including coping behaviors and team strategy. While the results are specific to the present simulation paradigm, this work presents compelling results that indicate how individual's problem-solving behaviors may affect a team's performance. Future work may involve conducting more detailed simulations as they relate to the intricacies of human problem solving, and further validating results with human subjects research.

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