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COLLABORATING WITH STYLE: USING AN AGENT-BASED MODEL TO SIMULATE COGNITIVE STYLE DIVERSITY IN PROBLEM SOLVING TEAMS

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ABSTRACT

Collaborative problem solving can be successful or counterproductive. The performance of collaborative teams depends not only on team members' abilities, but also on their cognitive styles. Cognitive style measures differences in problem-solving behavior: how people generate solutions, manage structure, and interact. While teamwork and problem solving have been studied separately, their interactions are less understood. This paper introduces the KAI Agent-Based Organizational Optimization Model (KABOOM), the first model to simulate cognitive style in collaborative problem solving. KABOOM simulates the performance of teams of agents with heterogeneous cognitive styles on two contextualized design problems. Results demonstrate that, depending on the problem, certain cognitive styles may be more effective than others. Also, intentionally aligning agents' cognitive styles with their roles can improve team performance. These experiments demonstrate that KABOOM is a useful tool for studying the effects of cognitive style on collaborative problem solving.

1 INTRODUCTION

Cognitive style can play an important role in collaborative problem solving [1], but its effects are not well understood. Cognitive style is defined as an individual's preferred manner of managing structure as they solve problems, make decisions, and seek to bring about change. In one of the few studies examining interactions of cognitive style with team problem-solving performance, Hammerschmidt [2] found that aligning team members' cognitive styles with tasks improved performance. This suggests that if the effects of cognitive style were better understood, the formation of engineering teams could be informed by the cognitive style of team members, as well as their domain expertise and ability. This paper addresses a gap in design research by studying the effects of cognitive style on collaborative problem solving using an agent-based model.

Most previous research on collaboration and team performance is based on qualitative descriptions of small studies [3], as large in-vivo studies over long periods of time are expensive. The results of these small-scale studies are difficult to generalize and tend to be applicable only in specific contexts [4]. Computational methods can be used to supplement traditional behavioral studies, advancing the pace of scientific development and providing better tools for managers. Specifically, agent-based models can provide rapid insight into the effects of team composition and structure on team performance, which enables the comparison of many different team scenarios [5]. Several recent publications demonstrate that simulation can be an effective tool for studying human systems in engineering design [4, 6–9]. Because human systems are messy and hard to decompose for scientific study, simulations like these are useful for isolating independent variables when studying cognition and social interaction [10].

However, translating the results of computational experiments to a real-world context can be challenging, especially when the simulated problem and environment are abstract. Some

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existing models of engineering teamwork incorporate contextualized, real-world problems [6, 8, eg], while others use more abstract objectives [10, 11, eg]. Abstract problems offer simplicity and flexibility, which can mean less development time and faster simulations. An abstract problem can also be modified arbitrarily because it is not tied to physical systems, so one abstract problem can have infinite variations (for instance, a parabolic objective function could have any linear and quadratic coefficients). However, abstract problems often lack the complex multivariate interactions and constraints of real-world problems. Using an abstract objective makes it difficult to tie meaning to performance, but the results of a contextualized problem can be directly compared to real-world outcomes. Ideally, simulations should closely reflect real-world problems and scenarios so their results can be compared directly to the performance of human teams. This paper implements two contextualized problems (a simple beam-design problem and a multi-objective race car-design problem) in order to evaluate the performance of simulated teams in an agent-based model.

Additionally, modeling human systems is difficult because human problem solvers are diverse, unpredictable, and sometimes irrational. Some problem-solving traits can be captured by cognitive style, a construct defined by cognitive preferences for managing structure in problem solving and social behavior [12]. While some agent-based models have attempted to reflect certain human qualities such as emotion, social status, and stress [10, 11, 13, 14], none have created agents with diverse cognitive styles.

One extensively validated instrument of cognitive style is the Kirton Adaption-Innovation inventory (KAI) [15]. The KAI uses 32 items to place individuals on a continuous spectrum of cognitive preference for managing structure, with two equally-valued extremes (highly adaptive and highly innovative) [12]. In general, more adaptive individuals prefer more structure in their problem solving, and seek consensus with other members of the team. In contrast, more innovative individuals prefer less structure in their problem solving and are less concerned about consensus. In practice, a more adaptive person tends to modify systems and solutions using incremental changes to make improvements, while adhering to existing structures and norms. A more innovative person, on the other hand, tends to make radical and riskier changes to systems and solutions with less regard for structures, norms, and the practical quality of the result. It is important to note that cognitive style is independent of cognitive level or ability [12, 15], so people of a particular style will not automatically be better or worse at solving problems. The model in this paper creates heterogeneous agents with diverse cognitive styles in order to study the effects of cognitive style on team problem-solving behavior.

In addition to a total score that represents a person's overall cognitive style, KAI also identifies three style sub-factors, called Sufficiency of Originality (SO), Efficiency (E), and Rule/Group Conformity (RG), which describe specific aspects of that style. Sufficiency of Originality relates to the paradigm-relatedness and immediate applicability of solutions that a person offers. More adaptive people tend to offer fewer solutions (based on their internal filtering for practicality, not capacity) that preserve and modify existing structures, and that are easier to integrate into previous work. More innovative people tend to offer a larger number of solutions (based on their looser criteria for acceptable solutions) that stretch or challenge existing structures and norms, and which may not fit easily into the current way of doing things. Efficiency relates to an individual's preferred methodology and attention to detail in solving problems. More adaptive individuals carefully evaluate their solutions to ensure they makes things better, while more innovative individuals tend to introduce riskier and less well-defined changes. Rule/Group Conformity relates to an individual's tendency to adhere to rules, norms, and structures, and to seek or resist group cohesion. Adaptive individuals prefer to leverage existing rules, norms, and constraints, while innovative individuals tend to ignore or actively violate them. In a group, adaptive individuals actively seek group cohesion, while innovative individuals tend to stray from or actively diverge from a group, which can create discord.

The overarching objective of this work is to use agent-based modeling to identify how cognitive style affects collaborative problem solving. To do this, we use the KAI Agent-Based Organizational Optimization Model (KABOOM), which we developed as the first computational tool to study the role of cognitive style in collaborative problem solving. Four specific research questions motivate the computational experiments in this paper:

1. How do the cognitive styles of team members impact team performance on different contextualized problems?
2. In a specialized team, what are the optimal cognitive styles for each sub-team?
3. Can strategically assigning agents to sub-problems based on their cognitive style improve the team's performance?
4. How does changing the decomposition of a problem affect the team performance?

The remainder of this paper summarizes relevant work in agent-based modeling, describes the KABOOM agent-based model with cognitive style and two contextualized problems, and discusses the computational experiments addressing the research questions noted above.

2 BACKGROUND

An agent-based model is a collection of autonomous agents that make decisions based on given rules [16]. Agents make runtime decisions about their actions and collaboration based on limited knowledge of their environment, limited decision-making capabilities, and limited ability to connect and share information with other agents [13, 17]. Agent-based models that solve contextualize problems can be constructed by modifying multi-agent optimization techniques such as simulated annealing (as in [8]) or a cooperative coevolutionary algorithm (as in [6]). This paper's methodology is based on simulated annealing [18], an optimization technique that gradually transitions from a stochastic to deterministic downhill search. In order to model realistic individual and group behavior, the agents should be designed to behave like humans as much as possible (rather than being designed for ideal optimization performance) [13].

Several agent-based models study specific individual and social aspects of the problem-solving process. In 2004, Tsvetovat and Carly [13] implement learning, social network theory, and social psychology in a multi-agent system to study social and technological systems. Martinez-Miranda et al. [14] develop an agent-based model to simulate the social and emotional aspects of team problem solving. Their model uses constructs of emotion, personality, and cognition to inform agent interaction. Other models focus on the effects of stress and motivation [11] or transactive learning as a product of communication [10]. Fan and Yen [19] review several other models that simulate emotion and sentiment. However, the authors are not aware of any existing models of teamwork that have heterogeneous agents with individual cognitive styles.

The model in this paper draws inspiration specifically from two recent models. First, the Cognitively-Inspired Simulated Annealing Teams (CISAT) model [8] provides a framework for studying the effects of problem characteristics on the optimal team process and team characteristics. CISAT's organic interaction timing and breadth versus depth solution search are recreated in KABOOM. The second direct inspiration is the work of Zurita et al. [6], which presents an agent-based model specifically created for a contextualized problem of designing a race car for the Society of Automotive Engineers (SAE) competition. Zurita et al. demonstrate that team specialization and problem decomposition can be represented by distributing the design parameters of a problem among sub-teams in an agent-based model. The current paper uses the same strategy for problem decomposition and also recreates the contextualized race car design problem from Zurita et al. [6].

In the context of design research, communication often refers to the exchange of solutions between individuals [10]. The way in which design teams communicate can be an important predictor of success [10, 20, 21]. Previous agent-based models have simulated communication with varying degrees of detail. In Tsvetovat and Carly [13], the probability that two agents will interact during a given iteration depends on their degree of similarity and social proximity. In contrast, agents created in Singh et al. [10] have limited ability to connect with other agents based on the structure of the team. The model in this paper takes a simpler approach to communication, where interaction probability is a global constant and agents interact with any other agent in their team without social preferences. This approach allows the simulation to capture important behaviors such as solution sharing and group convergence without adding unnecessary complexity to agent behavior that could increase noise in the results and obscure the effects of cognitive style.

Though communication is critical in teamwork, more does not mean better. Patrashkova-Volzdoska [21, 22] observes a trade-off between communication frequency and individual work: communication can aid performance up to a certain point, after which increasing communication can decrease team performance. Bernstein et al. [23] showed that intermittent (rather than constant) collaboration can provide the benefits of constant collaboration, as well as the benefits of individual work. In some cases, zero communication yields optimal performance [7, 24]. It is important to note that these results are often highly problem dependent.

In addition to communication, team composition is critical for team performance [9]. Composition refers to team size, lifespan (one project or several), location (local or geographically distributed), structure (flat or hierarchical), and diversity (homogeneous or heterogeneous) [10]. A flawed team composition can result in negative consequences for performance and social interactions [9]. Cognitive style, which we model in this work, is a critical aspect of team composition, and is used to define the cognitive diversity (homogeneity or heterogeneity) of the team [12]. Team composition should consider not only the personal traits of individuals, but also the alignment of those traits with the requirements of the problem [25]. Both domain expertise [26] and cognitive style [12] are important factors in aligning individual traits with problem requirements, but there is little evidence regarding how cognitive style influence a team's success. Martinez-Miranda and Pavón [9] state that although some human resources departments use tests of personality and cognitive level,

> It could be even more useful for project managers to apply the results of cognitive and psychological tests to build virtual teams and simulate their possible behaviors in order to analyze what could happen when people with specific characteristics interact with each other and with their respective tasks over the entire duration of a project. [9]

Therefore, this research aims to fill a gap at the intersection of cognitive style and agent-based modeling by incorporating cognitive style characteristics into an agent-based model of engineering teamwork.

3 METHODS

This paper introduces KABOOM (KAI Agent-Based Organizational Optimization Model), a new agent-based model designed to study the effects of cognitive style on team processes and performance. A Python implementation of KABOOM[1] is available under the MIT license [2] KABOOM simulates team problem solving by executing a modified multi-agent simulated annealing [18] optimization algorithm. Over the course of a simulation, a team of agents concurrently explores a design space to maximize an objective function. The key feature of simulated annealing that makes it useful for simulating human problem-solving behavior is that it begins as a stochastic search, but gradually transitions to a downhill search throughout the course of the simulation. This transition from breadth (exploring solutions) to depth (refining a solution) reflects actual human problem solving very well [8, 27, 28]. In KABOOM, there are three main modifications from a basic simulated annealing algorithm: (1) heterogeneous agents possess unique cognitive styles that modify their exploration of the solution space; (2) teams of agents specialize by decomposing a problem into sub-problems; and (3) agents communicate to share solutions in pair-wise and team-wide meetings (see model outline in Fig 1). The implementation of each of these modifications in KABOOM is described below. Together, they form a model that simulates the problem-solving process of a design team in order to investigate how style, communication, and specialization impact performance.

The team is defined as a set of agents that explore the same solution space and attempt to maximize the same objective function. Each agent is a software object that contains a current solution, memory of past solutions, and a KAI style composed of a total score and three sub-scores. Agents also have a current speed (new solution step size) and temperature (stochastic search parameter of simulated annealing), which decay geometrically at each iteration. For each iteration in the simulation, each agent either explores a new solution or communicates with another agent by attempting to share solutions. At a fixed interval (e.g. every 50 iterations), the entire team has a meeting that results in all agents converging to one solution. The following sections describe the implementation of each of these behaviors.

3.1 Cognitive Style

In KABOOM, each agent is instantiated with a cognitive style represented by a total KAI score and three sub-scores (SO, E, R/G). These attributes modify how the agent explores the solution space. Each style implementation described below is intended to simulate one aspect of how cognitive style manifests in a human's approach to problem solving. Cognitive style impacts behavior in varied and complex ways. Rather than trying to produce a complex, comprehensive, all-encompassing model, the current work captures only a few important aspects of the complex reality of a human system.

When an agent explores a new solution, it chooses a direction of travel randomly and moves a distance D from the current solution. It then evaluates the objective function at the new candidate solution. The distance D to the new solution is generated with a chi distribution χ and scaled by the agent's current speed s (i.e., $D = s \cdot \chi$). An agent's total KAI score determines its starting speed s_0 according to :

$$s_0 = \mu_s + \kappa \cdot \sigma_s \tag{1}$$

where μ_s and σ_s are the average and standard deviation of starting speed for all agents, and κ is the standardized total KAI score (re-scaled to a population mean of zero and standard deviation of one).

Therefore, while the exact distance to a candidate solution is stochastic, more adaptive agents generally move in smaller steps, and more innovative agents generally move in larger steps. All agents geometrically shrink their step size throughout the simulation, but the rate of decay also depends on style (see our discussion of Efficiency in Section 3.1.3.

When evaluating a candidate solution, an agent's perception of the solution quality is modified by its Sufficiency of Originality (SO) and Rule/Group Conformity (RG) sub-scores. The Efficiency (E) sub-score modifies the generation of new solutions rather than perceived solution quality (see Section 3.1.3). The perceived solution quality $f_P(\vec{x})$ is the sum of the true solution quality $f(\vec{x})$ (given by the objective function) with the SO preference P_{SO} and RG preference P_{RG} for the candidate solution:

$$f_P(\vec{x}) = f(\vec{x}) + P_{SO} + P_{RG} \tag{2}$$

The following two sections describe how the Sufficiency of Originality preference P_{SO} and Rule/Group Conformity preference P_{RG} are determined.

3.1.1 Sufficiency of Originality

The implementation of the SO sub-score reflects the preference of adaptors (low SO score) for paradigm-preserving solutions and the preference of innovators (high SO score) for paradigm-breaking solutions. The P_{SO} term measures whether a candidate solution is paradigm-preserving (moving toward the agent's previous solutions) or paradigm-breaking (moving away from the agent's previous solutions). First, an agent's memory of a previous solution is represented as a weighted average of all of the agent's previous solutions:

$$\vec{v}_{mem} = \sum_{n=1}^{N} (\vec{x} - M_n) * Q(n) \tag{3}$$

where $\vec{x}$ is the current solution, N is the number of memories (previous solutions) an agent has, and M_n selects each of the previous solutions in memory. The memory weights $Q(n)$ follow

[1] https://github.com/THREDgroup/kaboom/releases/tag/v1.1-beta
[2] https://choosealicense.com/licenses/mit/

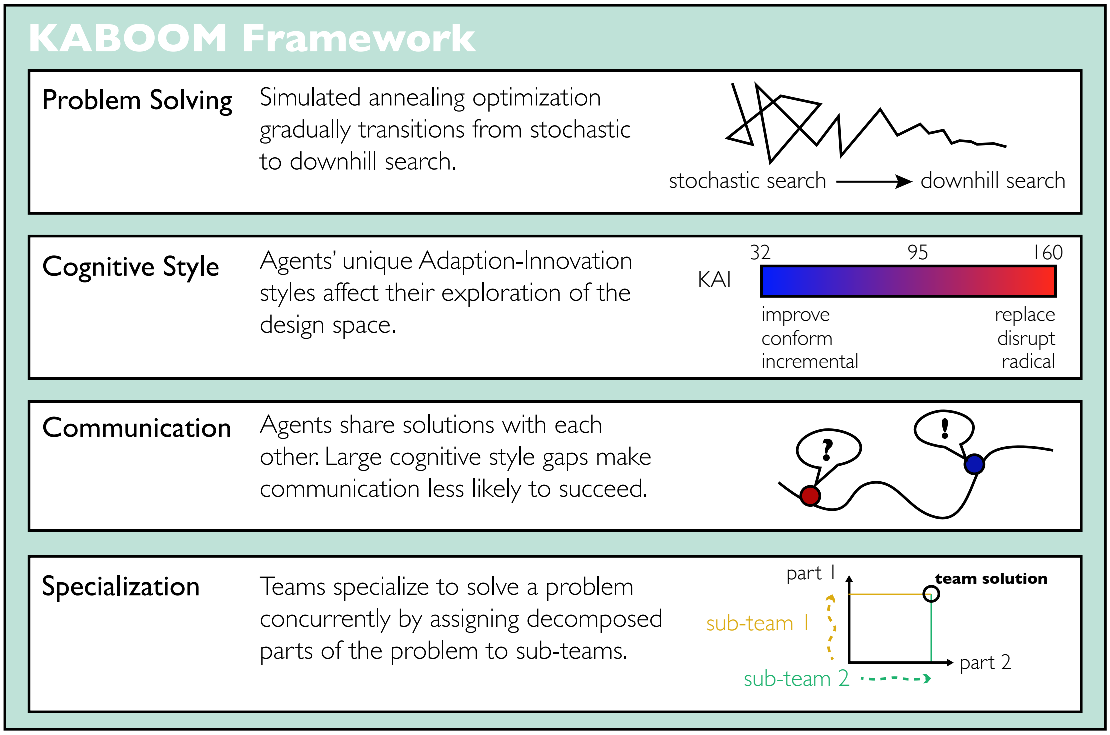

FIGURE 1. THE KAI AGENT BASED ORGANIZATIONAL OPTIMIZATION MODEL (KABOOM) IS BASED ON SIMULATED ANNEALING, WITH THE ADDITION OF COGNITIVE STYLE, COMMUNICATION, AND SPECIALIZATION. FIGURE REPRODUCED FROM [29].

a u-shaped curve to reflect the serial position effect [30], which states that people remember early memories and recent memories more easily than intermediate memories.

The paradigm relatedness Ω is a dot product of the vector from the current solution to the memory position $\vec{v}_{mem}$ and the current solution to the candidate solution $\vec{v}_n$:

$$\Omega = \|\vec{v}_{mem} \cdot \vec{v}_n\| \tag{4}$$

The P_{SO} term is a product of a global SO scaling constant W_{SO}, the agent's standardized SO sub-score $SO*$ (re-scaled to a population mean of zero and standard deviation of one), and the paradigm-relatedness Ω:

$$P_{SO} = \Omega \cdot SO* \cdot W_{SO} \tag{5}$$

Thus, agents with more adaptive SO sub-scores ($SO^* < 0$) have a positive preference for solutions that bring them towards their memory and a negative preference for solutions that lead them away from previous solutions. More innovative agents ($SO^* > 0$) have the opposite preference, favoring solutions that lead them away from their previous memories. Figure 3 (A) demonstrates this effect for individual agents exploring a two-dimensional solution space defined by a sinusoidal objective function. The color of the background represents the solution score for an abstract objective function, from worst (yellow) to best (blue). Each path connects a series of solutions that one agent explored in the solution space, with the final solution marked by a diamond. Note that in Figure 3 (A) the more adaptive agent (blue path) explored a set of solutions close to each other, while the more innovative agent continuously moved away from previous solutions.

3.1.2 Rule/Group Conformity The implementation of the Rule/Group Conformity sub-score reflects the tendency of more adaptive individuals to prefer and leverage structure in personal and impersonal contexts, and more innovative individuals to ignore or reject these structures. Here, we focus specifically on preference for social structures, which highlights the tendency of more adaptive individuals to seek convergence in a group, while more innovative individuals tend to diverge from a group.

In KABOOM, the group conformity of a solution C measures whether a solution brings an agent closer to or further from its teammates' solutions:

$$C = \|\vec{v}_{team} \cdot \vec{v}_n\| \tag{6}$$

where $\vec{v}_{team}$ is the vector from the current solution to the centroid of all team members' current solutions, and $\vec{v}_n$ is the vector from the current solution to new solution (as before). The P_{RG} term is a product of a global RG scaling constant W_{RG}, the agent's standardized RG sub-score RG^* (re-scaled to a population mean of zero and standard deviation of one), and the group conformity C:

$$P_{RG} = C \cdot RG^* \cdot W_{RG} \tag{7}$$

This preference leads more adaptive agents ($RG^* < 0$) to be more likely to accept solutions that move them toward the group's mean position and less likely to accept divergent solutions; this leads to group convergence. Conversely, more innovative agents ($RG^* > 0$) are more likely to accept divergent solutions and reject convergent solutions, which leads to group divergence. Figure 4 shows the effects of the Rule/Group Conformity style sub-factor on agents exploring a two-dimensional solution space. As in Figure 3, background color represents solution quality for an abstract objective with the worst scores in yellow and best scores in blue. Note that the more adaptive team (blue) converges to a shared solution while the more innovative team (red) diverges, with each agent ending at very different solutions.

3.1.3 Efficiency

Once an agent has evaluated a new solution, it must choose whether to accept the new solution (move to that position in the solution space) or discard it. If the agent perceives the candidate solution as better than the current solution (i.e., the perceived quality of the new solution $f_P(\vec{x}_n)$ is higher than the true quality of the current solution $f(\vec{x})$), it is always accepted. Otherwise, the agent stochastically determines whether to accept the new solution according to the probability established in simulated annealing:

$$P_{accept} = \exp\left(\frac{f(\vec{x}_n) - f(\vec{x})}{k_B T}\right), \quad f(\vec{x}_n) < f(\vec{x}) \tag{8}$$

The agent's Efficiency sub-score determines its starting temperature according to

$$T_0 = \mu_T + E^* \cdot \sigma_T \tag{9}$$

where E^* is the standardized Efficiency sub-score (re-scaled for a mean of zero and a standard deviation of one), and μ_T and σ_T are the mean and standard deviation of the starting temperature of all agents. Therefore, agents with higher (more innovative) E sub-scores apply more stochastic decision making behaviors, while agents with lower (more adaptive) E sub-scores are more concerned with the quality of new solutions.

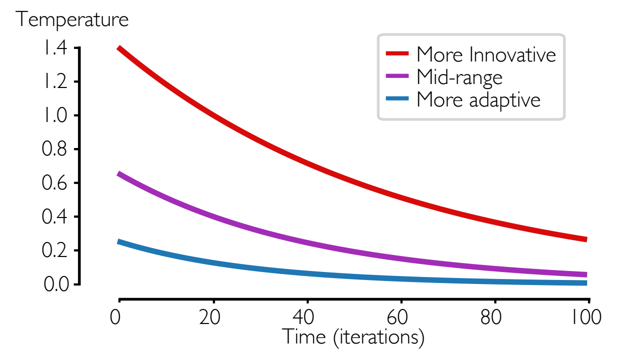

FIGURE 2. COOLING SCHEDULES FOR AGENTS WITH DIFFERENT EFFICIENCY (E) KAI SUB-SCORES

Additionally, the Efficiency sub-score affects the *rate* of geometric decay for temperature and speed during the simulation by determining the agent's ratio of start temperature r_0 to final temperature r_f according to the equation

$$\frac{r_0}{r_f} = \frac{1}{e^{2-E^*}} \tag{10}$$

This ratio is constrained to the range $[10^{-10}, 1]$, and is used for the decay of both temperature and speed. Figure 2 shows the temperature over the course of a simulation for an agent with a more innovative (high E), mid-range (mid-range E), and more adaptive (low E) Efficiency sub-score.

The result is that more adaptive agents converge to a solution quickly and spend time refining that solution, while more innovative agents explore broadly and may never converge to a refined solution. Figure 3 (B) demonstrates the effect of Efficiency style on agents' exploration of a two-dimensional design space by drawing agents' paths through the solution space. Note that the more adaptive agent (blue) made smaller changes between subsequent solutions while the more innovative agent (red) took larger steps.

3.2 Problem Decomposition

A problem of several variables can be decomposed by assigning subsets of the variables to different groups of agents, called sub-teams. Each sub-team owns a set of specialized dimensions that are a subset of the entire solution space. The agents on a sub-team only modify the variables belonging to their specialized sub-teams. The decomposition of the problem may

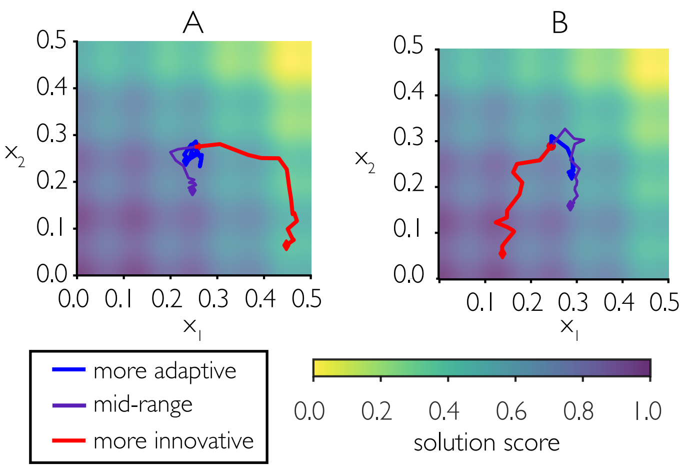

FIGURE 3. (A) EFFECT OF SO SUB-FACTOR ON EXPLORATION (B) EFFECT OF E SUB-FACTOR ON EXPLORATION

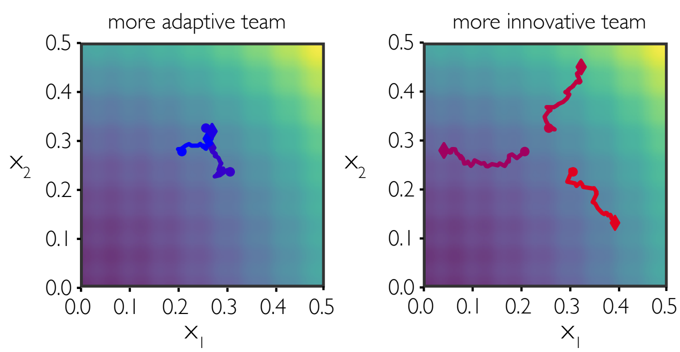

FIGURE 4. THE RG SUB-FACTOR LEADS AGENTS TO CONVERGE (MORE ADAPTIVE) OR DIVERGE (MORE INNOVATIVE) FROM THEIR TEAM IN THE SOLUTION SPACE

be arbitrary or may align with semantically related variables. Likewise, the assignment of agents to sub-teams may be arbitrary or intentional.

3.3 Agent Communication

In KABOOM, agents communicate by sharing their solutions in pairwise interactions and team meetings. Pairwise interactions occur organically at a frequency set by the global communication rate c, while team meetings occur at fixed intervals. Within each iteration, every agent decides to communicate with probability c or explore individually with probability $1-c$. Agents that decide to communicate are paired and attempt to share their solutions with each other. However, a gap in cognitive style between two agents makes it more difficult to communicate solutions [12, 31]. The probability P of successful communication between two agents with a cognitive gap (difference in KAI score) ΔKAI is

$$P = 1 - (\Delta KAI - 10)/170 \tag{11}$$

Communication is always successful for a cognitive gap less than 10 points, the just-noticeable-difference for KAI [12], then becomes gradually more likely to fail as cognitive gap increases. If communication is successful, the agents receive each other's solutions and decide whether to accept or reject them according to Eqn. 8. If communication is not successful, the agents receive no information and do not make progress in that iteration.

Team meetings occur every 50 iterations and result in all agents on the team converging to one solution. First, each sub-team finds the best solution of any of its agents. Then the team forms a composite solution by taking each sub-team's specialized dimensions from that sub-team's best solution. Finally, all agents accept the team's composite solution and begin working from it.

3.4 Contextualized Problems

KABOOM can model any problem that can be expressed using an objective function of a finite number of continuous variables. In order to contextualize the results of the model in a real-world context, this paper implements two contextualized problems: a relatively complicated race car design problem and a simpler I-beam design problem. The implementation of their objective functions is described below.

3.4.1 Race Car Design Problem

The first contextualized problem is the design of an SAE race car, which was formulated by Zurita et al. [6] to evaluate multi-agent coordination on a decomposed problem. We use the same problem with minor modifications in order to evaluate team performance using KABOOM. In this section, we only provide general information on the implementation of the problem for KABOOM; the reader is referred to the original publications for the remaining details.

The race car design problem parameterizes the design of a racing vehicle into 56 variables, which are divided among eleven sub-systems, such as brakes, engine, and front suspension (see Figure 5). Agents belong to one of eleven sub-teams, one team for each sub-system. Therefore, each agent explores the solution space only in the sub-space of their team's dimensions (i.e., an agent on the brakes team only modifies the brakes variables). In order to allow a variety of styles on each sub-team without excessive computational costs, each sub-team in the simulation has 3 agents (33 agents on the entire team). The performance of the team is evaluated based on a global objective function, which is composed of eight sub-objectives, each describing an appropriate metric, such as acceleration, breaking distance, or turning radius. After standardizing the performance on each sub-objective (rescaling to a mean of zero and standard deviation of

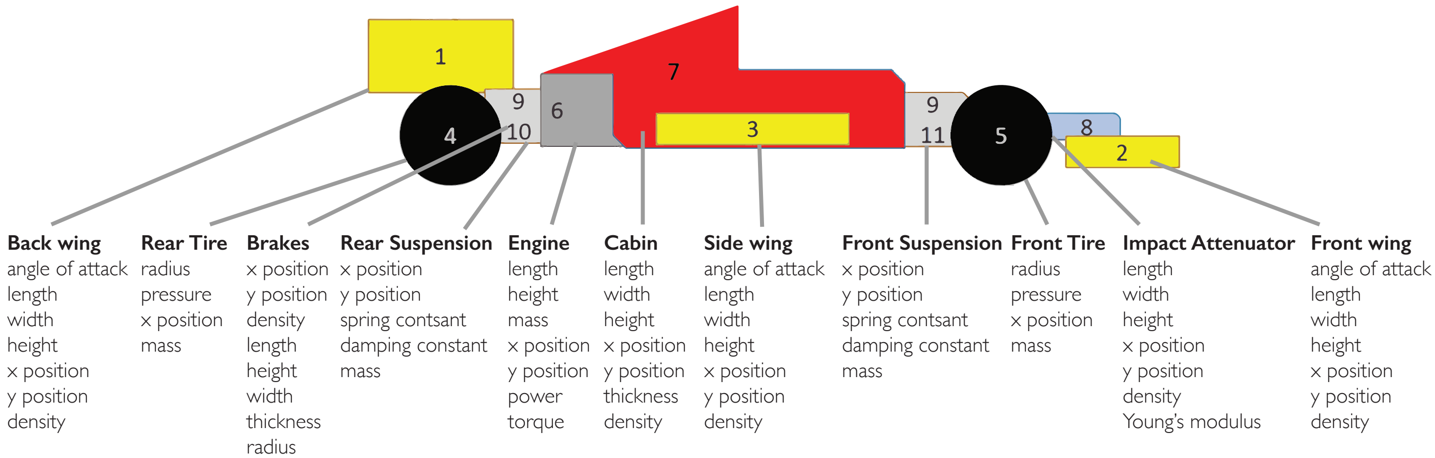

FIGURE 5. THE VARIABLES IN THE CAR DESIGN PROBLEM ARE DISTRIBUTED AMONG SPECIALIZED TEAMS. FIGURE ADAPTED FROM ZURITA ET AL. [6] FIG. 3 AND TAB. 1.

one), the total objective score is calculated as a weighted sum of the sub-objective scores. This paper uses Weight Scenario 2 of Zurita's three weighting schemes ([6] Table 2) for the weighted sum of sub-objectives to form a scalar objective function. See Zurita et al. [6] for a full description of the dimensions, sub-objectives, and constraints of the race car design problem.

In order to maintain a continuous solution space for the KABOOM model, discrete-valued variables are mapped onto a continuous space by selecting one driving dimension for each discrete variable. When the objective function is evaluated, the variable is mapped back onto the nearest feasible discrete value. For example, the choice of material for the race car cabin is a discrete-valued variable and is chosen from a table that lists density and modulus of elasticity for several materials. We select density as the driving variable and represent material density as a continuous variable in the solution space. When an agent evaluates the objective function, it chooses the material with density nearest to the current continuous value. Besides material choice, the only discrete-valued variables are related to the engine (driving dimension is power) and the wheels (driving dimension is radius).

Additionally, the solution space is normalized to a unit cube, so that agents can explore each dimension equally. The minimum and maximum values of each parameter are used to re-scale the feasible space to the interval [0,1]. Thus, feasible solutions to the problem are vectors of length 56 with values in [0,1]. This normalized vector is re-scaled into real-world units when evaluating the objective function (which is implemented in SI units).

3.4.2 Beam Design Problem

This section describes an objective function for designing a wide-flange beam in order to compare the design of a complex system (the race car) with

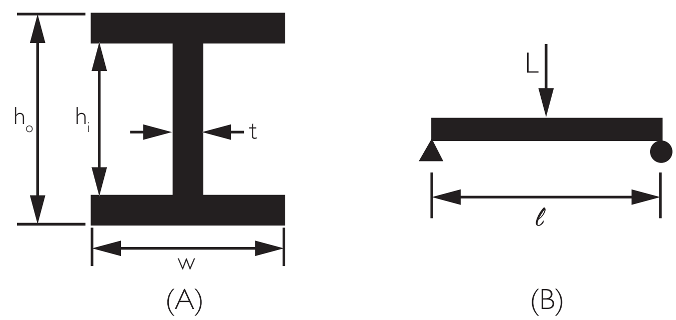

FIGURE 6. DESIGN DIMENSIONS OF BEAM CROSS SECTION (A) AND BEAM LOADING (B)

a simpler design problem (the beam). The beam design problem has four design variables related to beam geometry (Fig 6 A) and an objective of minimizing the maximum stress and displacement for a fixed load. The beam is simply supported, with fixed length and a point load at the center (Fig 6 B). The equations used here can be found in Gere's Mechanics of Materials [32].

The objective function is a weighted sum of maximum stress and displacement:

$$f(x) = \delta^*(x) \cdot 10^3 + \sigma^*(x) \cdot 10^{-6} \tag{12}$$

where $\delta^*(x)$ is the maximum displacement of the beam

$$\delta^*(x) = \frac{-Ll^3}{48EI} \tag{13}$$

and where L is the center point load, l is the length of the beam,

E is the modulus of elasticity, and I is the moment of inertia calculated with

$$I = \frac{1}{12}\left[w(h_i^3 - h_o^3) + t(h_i^3)\right] \tag{14}$$

Because the extreme fibers of the beam are located a distance $h_o/2$ from the central axis, the maximum stress σ^* is given by

$$\sigma^* = \frac{h_o L l}{8I} \tag{15}$$

where L is the center point load, l is the length of the beam, and I is the moment of inertia. In this paper, the load L is 50,000 Newtons (N), the beam length is 5 meters (m), and the modulus of elasticity is 200 gigapascals (GPa). The starting values for the design variables (in meters) are $h_i = 0.23$, $h_o = 0.25$, $w = 0.1$, and $t = .02$.

All dimensions are constrained to the range $[0.007, 1]$ meters, and the horizontal flange thickness (i.e. $(h_o - h_i)/2$) is also constrained to this minimum thickness. Additionally, the total area of the cross section is constrained by a maximum value of 0.007 m^2. This is equivalent to a mass constraint because of the prismatic geometry.

4 RESULTS

This section discusses the results of computational experiments that address our four research questions with KABOOM by testing team performance with respect to different cognitive style team compositions. The first experiment tests how different cognitive styles perform on each problem. Cognitive style is independent of cognitive level, and no cognitive style is better than another in general. Still, in some specific problems, individuals of certain cognitive styles may perform better than others. For instance, innovators may perform better than adaptors on design problems focused on new product development which require broad exploration (e.g. designing a new children's toy) while adaptors may perform better than innovators on improvements of existing designs, which require thorough local exploration (e.g. improving the efficiency of an internal combustion engine).

The first computational experiment creates homogeneous teams (i.e., all agents on a team have the same cognitive style) and tests them on both the beam design and car design problems. For the beam design problem, this involved an 8-agent team in a 100-step simulation, specialized into 2 sub-teams of 4 agents each (each sub-team controls two of the four design dimensions). Figure 7 (top) shows that changing the shared cognitive (KAI) style of the homogeneous team did not impact performance on the beam design problem. The car design problem is

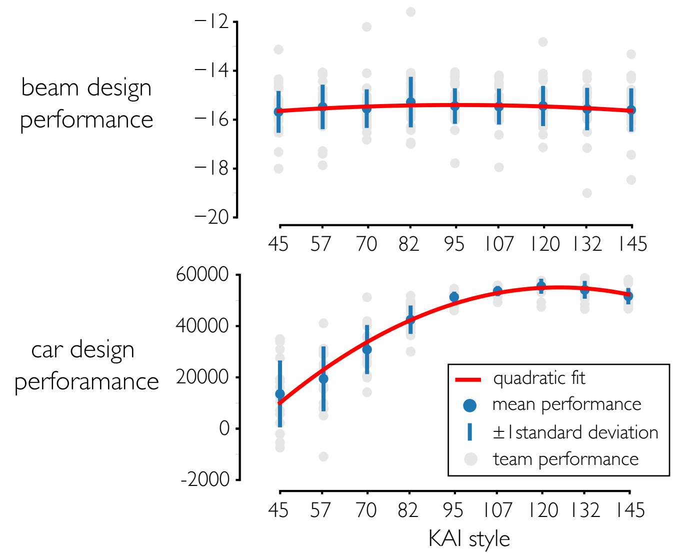

FIGURE 7. STYLE DID NOT AFFECT PERFORMANCE IN THE BEAM DESIGN PROBLEM. FOR THE CAR DESIGN PROBLEM, TEAMS OF MORE INNOVATIVE AGENTS PERFORMED BETTER.

significantly more complicated, with a 33-agent team decomposing the 56-variable problem into 11 sub-problems (11 sub-teams of 3 agents each), also with a 100-step simulation. For this problem, the shared cognitive style of the team had drastic effects on performance, with the more innovative teams outperforming the more adaptive and mid-range teams (Figure 7, bottom). Each figure shows a quadratic regression fitted to the results. A quadratic regression is used because it is the simplest fit that can capture how performance peaks at a specific cognitive style.

Though there are no human studies on these specific problems to compare our results to, the results demonstrate that some cognitive styles may be more or less effective for specific types of problems. It is of paramount importance to note that this different in performance is problem-dependent. There is no single cognitive style that is superior to all others across all problems. Therefore, a deeper understanding of cognitive style and its relationship to design problems is critical for appropriate managerial interventions within design teams.

In order to better understand how a team's cognitive style composition impacts performance in the race car design problem, our second experiment tests the sensitivity of each specialized sub-team to changes in cognitive style. All remaining experiments utilize the more complicated race car design problem. For each of the eleven sub-teams, the sub-team's style is varied while holding the style of the rest of the remaining sub-teams constant (all agents outside the sub-team in question have a mid-range style of 95). Figure 8 plots the results of this experiment. Quadratic regressions fitted to the results capture the response of sub-team to changes in cognitive style composition.

The results in Figure 8 demonstrate that each sub-team responds differently to changes in its cognitive style composition. For example, populating the impact attenuator team with more innovative agents improves overall team performance, while populating the rear suspension sub-team with more adaptive agents improves performance, and mid-range agents are the best style for the engine team. KABOOM does not model any aspect of domain expertise, and these results do not suggest that cognitive style is related to the level of expertise or ability for designing a certain aspect of the car. Rather, the results suggest a meaningful difference in the characteristics of the solution space for different parts of the car problem. For instance, the solution space explored by agents designing the rear suspension (where adaptive agents performed best) may be best suited for the incremental, detailed, "adaptive" search approach, while the solution spaces explored for the rear wing and impact attenuator (where innovative agents performed best) may be better suited for a more stochastic, "innovative" problem-solving approach.

Given that the sub-teams of the race car design problem had a variety of optimal cognitive styles, we can strategically assign agents to the sub-problems that are best-suited for their respective styles. The following experiment uses teams with organic composition, which means they are composed of agents randomly drawn from a virtual population. The virtual population reflects a realistic distribution of cognitive styles based on a data set of 597 individuals' KAI scores and sub-scores gathered in previous research [33]. In the control group teams, agents from the organic team are randomly assigned to sub-teams without regard for their cognitive style. In the experimental group of strategic allocation teams, agents are assigned to sub-teams based on their cognitive style. First, the agents are listed in order of ascending cognitive style, and the sub-teams are listed in order of ascending cognitive-style preference (accounting for the strength of the style effect, as well as the best style). This ordering is: Rear Suspension, Rear Tires, Brakes, Side Wing, Front Tire, Engine, Front Suspension, Front Wing, Cabin, Impact Attenuator, and Rear Wing. Then, the agents are assigned to the sub-teams according to the ordered lists (e.g., first three agents to first sub-team, etc). Figure 9 shows that the strategic teams outperformed the control group teams significantly (effect size $= 1.12$, $p < .05$).

Teams in both the control and strategic sets are composed of randomly chosen agents with respect to cognitive style. This demonstrates that strategically placing the right members of the team on the right sub-teams could significantly improve performance. This result is supported by a human study of team success and KAI cognitive diversity by Hammerschmidt [2], which found that teams had higher levels of success when tasks were coordinated with team members' KAI style. In real design teams, dimensions of cognitive level (e.g., disciplinary knowledge, experience, intelligence) are important factors in assigning members of a team to different parts of a problem. However, all else being equal, accounting for cognitive style when selecting people for different parts of a problem could improve a team's performance.

As demonstrated in Fig 5, the race car design problem decomposition follows semantic divisions that make sense in the real-world application (i.e., wheel variables "belong together" and cabin variables "belong together"). This leads to an uneven distribution of the variables across the eleven sub-teams. The fourth experiment compares this semantic problem decomposition to a "blind" problem decomposition, where the design variables are evenly distributed among eleven teams without grouping semantically-related variables (i.e., one team may design the rear wheel radius, cabin thickness, and angle of the front wing). The experiment held the number of agents (33), number of sub-teams (11), team composition (homogeneous mid-range KAI style of 95), and number of iterations (100) constant. The results in Fig 10 show that teams that used the blind problem decomposition significantly outperformed teams that used the semantic problem decomposition based on the car's systems (effect size $=$ 1.10, $p < .05$). In a human team, semantic problem decomposition would be critical to success, because problem solving depends on domain expertise and contextual knowledge. In the current KABOOM model, agents problem solve with no contextual or domain knowledge, which leads to the unrealistic boost in performance caused by redistributing the design variables. This suggests that incorporating some aspects of cognitive level (e.g., domain knowledge) in KABOOM is an important direction for future work. However, it also highlights the importance of equally distributing the human resources of a team across sub-teams in order to improve performance.

5 CONCLUSIONS

Cognitive style plays an important role in collaborative problem solving, but this key variable had not been modeled in previous simulations of teams solving problems. In this paper, KABOOM provided a simulation framework to study how the cognitive style composition of a team impacts performance on contextualized design problems. Using the model, we addressed four research questions:

1. **How do the cognitive styles of team members impact team performance on different contextualized problems?** On a simple I-beam design problem, changing the cognitive style composition of the team did not affect performance. For the more complicated race car design problem, homogeneous teams of more innovative style outperformed homogeneous teams of adaptive and mid-range style. These results illustrated that while no cognitive style is superior to another, a certain style may be advantageous for a specific design problem.
2. **In a team with specialized sub-teams, what are the opti-**

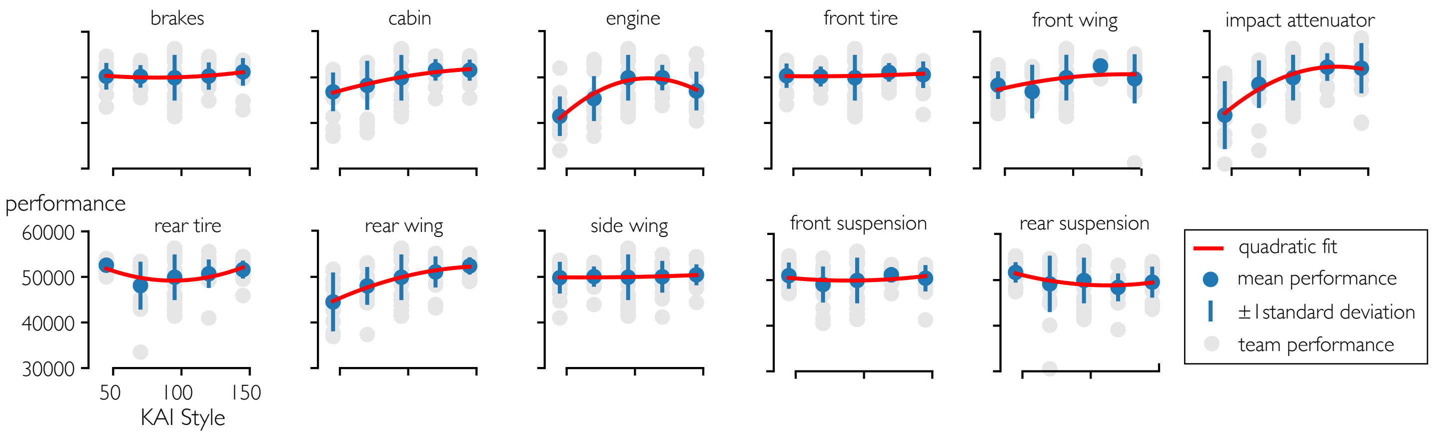

FIGURE 8. VARYING THE STYLE OF ONE SUB-TEAM WHILE HOLDING THE REST OF THE TEAM CONSTANT (HOMOGENEOUS MID-RANGE) REVEALS THAT ON SOME SUB-PROBLEMS A SPECIFIC KAI STYLE PERFORMS BEST.

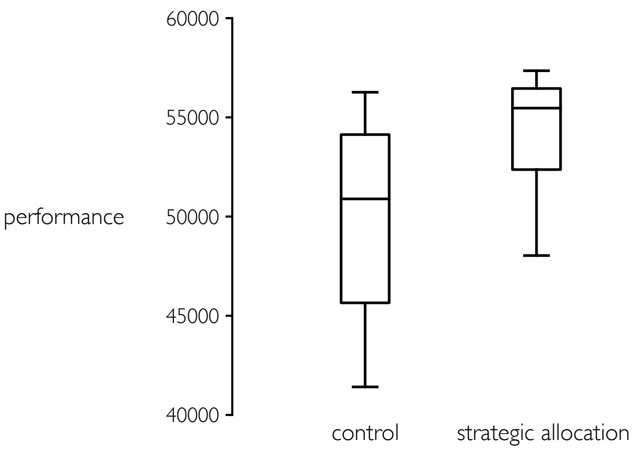

FIGURE 9. STRATEGICALLY ASSIGNING AGENTS OF AN ORGANICALLY COMPOSED TEAM TO SUB-PROBLEMS BASED ON COGNITIVE STYLE IMPROVES PERFORMANCE

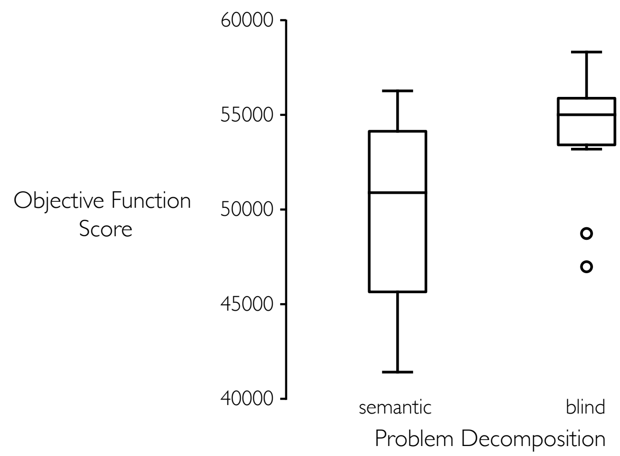

FIGURE 10. ASSIGNING VARIABLES OF THE CAR PROBLEM TO TEAMS RANDOMLY RESULTS IN BETTER PERFORMANCE THAN USING THE SEMANTIC PROBLEM DECOMPOSITION

mal cognitive styles for each sub-team? Studying the effects of cognitive style on each separate sub-team of the race car design problem revealed that each sub-team responded differently to changes in style composition. Although the best homogeneous style for the entire team was more innovative, there were sub-teams that benefited from more adaptive and mid-range style, as well as innovative styles. The effects of cognitive style also depend on the characteristics of sub-problems.

3. **Can strategically assigning agents to sub-problems based on their cognitive style improve the team's performance?** An experiment demonstrated that the performance of teams with organic composition (agents drawn randomly from a population) could be improved significantly by strategically assigning agents to sub-teams of the car problem based on the optimal style for each sub-problem. This suggests that understanding the cognitive styles of the members of a design team can be used to boost team performance.
4. **How does changing the decomposition of a problem affect the team performance?** Counter-intuitively, changing the decomposition of the car problem from the semantically informed decomposition to a blind, uniform distribution of variables across sub-teams improved performance. The computational problem-solvers lack contextual knowledge and domain expertise, so the random assignment of variables from different parts of the car was not detrimental to their performance. Future work should incorporate cognitive level into the KABOOM model in order to reflect the

importance of domain knowledge in collaborative problem solving.

As with any model, KABOOM does not attempt to fully capture the complexity of human behavior. Specifically, the model's reflection of communication and collaboration are relatively simple compared to some other models [10, 13, 19, 21–23]. In real teams people communicate ideas about process, strategy, sentiment, and emotion while agents in KABOOM only communicate their solutions. Another major limitation of this work is the lack of human subjects research to validate results. Without support from human-subjects studies, we cannot assume the results of the model will be valid in real-life scenarios.

Future work should include validation studies with human subjects, in order to test how the phenomena observed in computational experiments compare to real-world behavior. For instance, a human-subjects study could test whether strategically choosing team members for sub-tasks based on their cognitive style (as in Figure 9) improves team performance. In addition, human subjects studies will help to inform the refinement of the model. Observations of human problem-solving behavior will help to tune model parameters and highlight aspects of the model that should be improved or modified. As the first computational model of cognitive style in problem solving, KABOOM provides a flexible framework for computational simulations that be continuously adapted to more closely reflect the (sometimes strange) problem-solving behaviors of human beings.

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