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A Computational Model of Human Proficiency in Engineering Configuration Design

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This work introduces the Proficient Simulated Annealing Design Agent Model (PSADA), a cognitively inspired, agent-based model of engineering configuration design. PSADA models different proficiency agents using move selection heuristics and problem space search strategies, both of which are identified and extracted from prior human subject studies. The model is validated with two design problems. Agents are compared to human designers and show the accurate simulation of the behaviors of the different proficiency designers. These behavior differences lead to significantly different performance levels, matching the human performance levels with just one exception. These validated heterogeneous agents are placed into teams and confirmed previous findings that the most proficient member of a configuration design team has the largest impact (positive or negative) on team performance. The PSADA model is introduced as a scalable platform to further explore configuration design proficiency's role in design team performance and organizational behavior. [DOI: 10.1115/1.4062861]

Keywords: agent-based design, cognitive-based design, collaborative design, design teams, design automation

1 Introduction

Teams are the cornerstone of engineering organizations; however, much is unknown about how best to construct them. Several frameworks have been used to describe the team composition and creation process [1]. It is not disputed that the composition of individual team member attributes plays an important role in a team's performance. Still, there are inconsistent results on whether an attribute's minimum level, maximum level, variance, or average level is the best predictor of team success [2]. The relative contribution framework is one such framework and focuses on how individual team members affect team outcomes relative to the other members of the team [3]. A previous human subject study demonstrated how the proficiency of individual designers contributes to overall team performance in a configuration design problem [4]. It was found that the most proficient member had the most significant effect on team performance metrics, positive or negative. In short, the maximum level of proficiency on the team is the best predictor of team success. This means that increasing the proficiency of the most proficient member of a team has a larger effect than increasing the proficiency of any other team member by the same amount. While this result is insightful, the limitations of a human subject study constrain the conclusions that can be drawn. Because of the high time cost of a human subject study, a computational model of proficiency in engineering configuration design would be beneficial and complement the findings from human subject studies. With a validated computational model, the challenges of limited data and isolation of desired attributes of team members can be mitigated.

A single computational agent represents each designer in a multi-agent model. Autonomous agents are modeled such that they perceive their environment, exhibit goal-directed behavior, and are capable of interacting with other agents [5]. Multi-agent models have been used to model various aspects of design, including design organizations [6,7], design negotiation [8], optimal team structure [9], navigating disrupted design objectives [10], social learning in teams [11], and multidisciplinary design [12]. Recently, heterogeneous agents have been utilized to evaluate how varying characteristics of an individual agent affect team outcomes in multi-agent models of engineering design teams [13–15]. While many other multi-agent models have been used to solve various engineering problems, they are designed to either solve the problem or propose new design methods, not to model and study engineering design teams and their problem-solving strategies [16–18].

The objective of this work is to model proficiency in engineering configuration design. Configuration design is a class of design tasks where the artifact being designed is constructed from a set of predefined components and obeys a set of constraints [19,20]. A validated model can draw conclusions about how different proficiency designers should be utilized to construct design teams more effectively. Proficiency is a designer's ability to deal with a specific range of problem [21]. It is related to a person's general aptitude and the complexity of the task but is most strongly correlated with the person's experience with the task [22]. To model an attribute, there must be behavior differences for varying levels of that attribute. In the previous human subject study, high-proficiency designers moved quickly from design initialization to fine-tuning

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and optimization and spent less time building the topology of their design. Meanwhile, low-proficiency designers spent significantly more time developing a topology of their design before moving onto the optimization phase of the design process [4]. This finding fits the existing literature on expert versus novice designer behavior, which can translate to high and low proficiency. A well-established element of design expertise is a solution-focused approach. Experts move to a problem solution faster than less experienced designers and spend less time exploring the problem domain [23–25]. The other difference in behavior for various proficiency designers is that different proficiency designers utilize distinctive move selection heuristics [4]. These heuristics were explored using extracted hidden Markov models (HMMs), which are shown to model the sequential design process heuristics effectively [26]. These two findings can be modeled to create cognitively inspired computational agents that mimic the behavior of different proficiency designers and consequently mimic the performance of different proficiency designers.

In summary, this paper aims to introduce and validate a cognitively inspired computational model of proficiency in engineering configuration design. This model can serve as a platform for future experimentation to better understand individual team member proficiency and its effect on team performance. The model implementations described in this work are available to the public for educational and academic research purposes.[2]

2 The Proficient Simulated Annealing Design Agent Model

This work introduces the Proficient Simulated Annealing Design Agents (PSADA) model. The inspiration for this model is the cognitively inspired simulated annealing teams (CISAT) model introduced by McComb et al. [27]. Like CISAT, each PSADA agent uses the simulated annealing stochastic optimization method to dictate their design process [28]. Simulated annealing describes significant aspects of human problem-solving behavior [29] and has been used to computationally model human behavior on mechanical design problems [27,29]. PSADA differs from CISAT by modeling agents heterogeneously, with varying proficiency levels. To accomplish this goal, PSADA models agents using characteristics that focus on individual designer decisions in the design process. These characteristics are modeled after the behavior of individual designers identified from a previous human subject study. Specifically, two characteristics of individual designers are explicitly modeled to mimic those behavior differences for various proficiency designers. They are:

(1) **Design space search strategy—**Describes a designer's tendency to utilize breadth or depth search strategies based on proficiency [4,24].
(2) **Move selection heuristics—**Designers utilize past relevant experience to guide sequential design decisions [4,26,30].

Both characteristics and how they are modeled are discussed in detail in Secs. 2.1 and 2.2.

The different proficiency PSADA agents are validated against their equivalently proficient human designers on two engineering configuration design problems. After validating the different proficiency PSADA agents, they are placed into teams and interact in the same method as the human subject study. This team structure for configuration design problems mimics the team structure of sub-teams within a larger design team. For example, when a company designs a car, several sub-teams work on specific components, like the suspension, chassis, and powertrain. Each sub-team member can collaborate with their sub-team teammates but could realistically develop a solution independently.

[2]https://github.com/CMU-Integrated-Design-Innovation-Group

Figure 1 summarizes the structure of the PSADA model for both an individual agent and a team of agents. In the PSADA model, each agent can work on the entire problem. Each agent iteratively works to create a design, shares their solution with teammates at probabilistic, self-determined moments, and probabilistically chooses whether to adopt their teammates' designs when they are shared. This structure allows for individual agents to be modeled independently from their teammates; thus, the characteristics of individual agents and their effect on team performance can be analyzed. Agents complete all actions and decisions independently, and therefore, the model is easily scaled to include different numbers of agents on a team. Section 2.3 discusses the team-based characteristics in detail.

2.1 Design Space Search Strategy.

Analogous to high-proficiency designers, expert designers often move more quickly to a solution path [24]. Analogous to low-proficiency designers, novice designers often use a "trial-and-error" approach [31]. It is posited that these differences in design space search strategy are due to experience and understanding of the entire design space. High-proficiency designers can quickly make conjectures about solution paths. In contrast, low-proficiency designers must take time to attempt solution paths and make decisions only after they gain feedback from their attempts [4]. This key insight is one way in which proficiency is modeled in PSADA.

Human decision-makers rarely search until the optimal solution is found and instead search through available solutions only until relevant metrics are reached [32]. Simulated annealing is an optimization technique that does not, however, guarantee that the optimal solution is found. After every action the agents take, the simulated annealing algorithm accepts or rejects the move based on the quality of the new design versus the quality of the old design and the temperature parameter prescribed to the simulated annealing algorithm. If the design is better than the previous iteration, it is accepted. If the design is worse, the algorithm probabilistically accepts the design based on Eq. (1):

$$P_{\text{accept}}(q, q', T) = \exp\left(\frac{q - q'}{T}\right) \tag{1}$$

For this equation, q is the quality of the previous iteration, q' is the quality of the new iteration, T is the temperature parameter, and it assumed that $q' > q$. The temperature parameter in simulated annealing decreases based on a cooling schedule throughout the search process. The initial temperature for the algorithm depends on the objective function used.

Within PSADA, high-proficiency designers are modeled with a more aggressive simulated annealing cooling schedule to enable these designers to move more quickly to a deterministic solution path, which mimics how high-proficiency designers move more quickly to a solution path. Middle- and low-proficiency designers are modeled with decreasingly aggressive cooling schedules, which allows for an increasing amount of trial-and-error searches early in the design session. Because the length of the design session is equal for all designers, a more aggressive cooling schedule allows for more iterations on a deterministic path. A geometric cooling schedule is used for each and is shown by Eq. (2),

$$T' = T * c_{\text{p}} \tag{2}$$

where T is the temperature at the current iteration, T' is the temperature at the next iteration, and c_{p} is the cooling constant for the agents' proficiency. In PSADA, the cooling constants used are 0.9, 0.95, and 0.99 for the high-, middle-, and low-proficiency agents, respectively.

2.2 Move Selection Heuristics.

In any design process, designers use heuristics to guide them in solving the design challenge [33]. These heuristics are learned from past relevant experience with the task at hand. The move selection heuristics can be extracted using

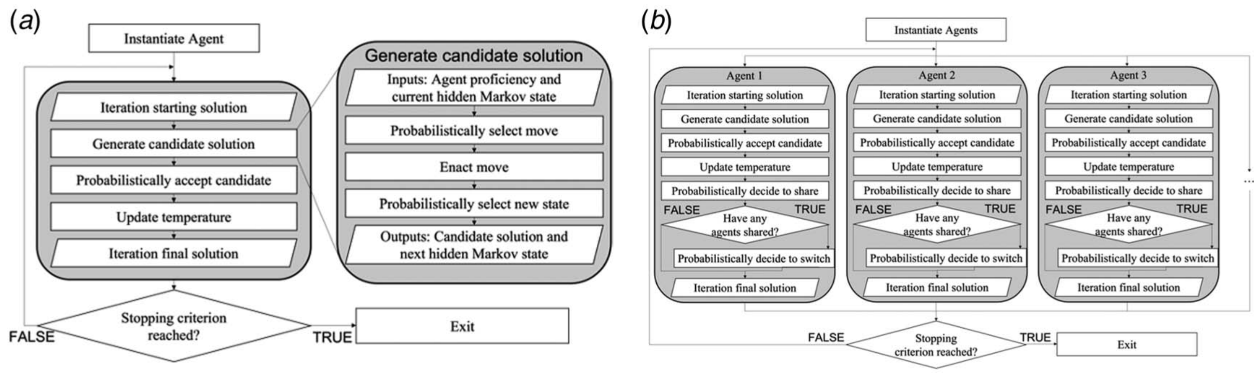

Fig. 1 (*a*) **Logic flowchart for an individual PSADA agent and** (*b*) **logic flowchart for PSADA team framework**

HMMs for a configuration design task [4,26]. An HMM represents a first-order Markov process with hidden states [34]. An HMM is represented by a transition matrix, **T,** and an emission matrix, **E**. After each step, the **T** matrix shows the probability of the next step being in each state. At each step, the **E** matrix shows the probability distribution for taking each action given the current state at that step. Experimental data are required to train an HMM for each level of proficiency. A PSADA agent will probabilistically select their action at each iteration, given their proficiency and current state. After each iteration, a PSADA agent will probabilistically transition to the next state, given their proficiency and current state.

A designer's proficiency at a design task is most strongly related to their experience with it [22]. In PSADA, each level of proficiency requires a unique HMM trained on past human behavior for that task. Therefore, the task-specific element of proficiency is captured by these move selection heuristics in the PSADA model.

2.3 Team-Based Characteristics. The PSADA model adopts team-focused characteristics from previous models of design teams that contribute to how agents solve problems as part of a team [27]. The modeling of each characteristic in PSADA is designed to focus on individual agent decision-making instead of team decision-making as in other models. Specifically, the communication in the PSADA model is designed so that agents independently determine when to communicate their solutions with their teammates, and their teammates assess other designs only when they are shared. The team-specific characteristics that are used in this model are:

(1) **Organic interaction timing—**Interaction occurs at irregular and self-determined intervals [35,36].
(2) **Quality bias reduction—**Individuals in a team develop multiple solution concepts to avoid premature convergence [37].
(3) **Self-bias—**Designers are biased toward their own solutions [38].

Team interaction in real engineering teams does not occur at regular intervals [35]. After each iteration, agents in the PSADA model probabilistically interact by deciding to share their current solution with their teammates. The probability of sharing is based on the agents' relative solution quality. Agents are more likely to share their current iteration if it is better than their previous iteration. This models organic interaction timing. A step function is used for determining the probability of sharing. This step function is shown by Eq. (3) and is determined from the previous human subject study where the overall rate of moves per share is matched. The step function is

$$P_{\text{share}}(q', q) = \begin{cases} 0.05, & q' - q < 0 \\ 0.1, & q' = q \\ 0.25 & \text{otherwise} \end{cases} \tag{3}$$

In Eq. (3), P_{share} is the probability of sharing the new solution, q' is the quality of the new solution, and q is the quality of the previous solution.

Individuals in a team develop multiple solution concepts to avoid premature convergence [37]. They tend to focus on the most promising alternatives but do not do so greedily [10]. When a design is shared within a team, the other agents on the team evaluate the design against their own and determine whether to adopt the shared design. Designers must make a binary choice. Quality bias reduction is modeled using logistic regression, which finds the probability of switching designs based on the quality of each alternative. Logistic regression is commonly used for discrete choice modeling. The form that is used for this study is shown by Eqs. (4) and (5), where the relative difference, δ_r, is found by

$$\delta_r = \frac{(q_s - q_c)}{q_c} \tag{4}$$

and the probability of switching is found by

$$P_{\text{switch}}(\delta_r) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 \delta_r)}} \tag{5}$$

In Eq. (4), q_s is the objective function value for the shared solution and q_c is the current objective function value for the agent. In Eq. (5), P_{switch} is the probability of adopting the new design, and β_0 and β_1 are the coefficient estimates.

Finally, designers have been found to favor their own designs, even when it is not the best option available to them [38]. Because PSADA models interaction as a binary choice using logistic regression, the probability of switching designs can determine if designers in the original human subject study favored their own designs and, therefore, whether the PSADA model incorporates self-bias.

3 Design Tasks

Proficiency is inherently task-specific. The PSADA model is tested on two different configuration design tasks to ensure that the model is generalizable for modeling proficiency across configuration design problems. Table 1 summarizes the parameters that are used for each problem.

3.1 Truss Design. The insights that inspired the PSADA model are from a previous human subject study conducted by Brownell et al., in which human designers ($n = 78$) were tasked with designing various truss structures that met specific constraints [4]. Previous studies have shown that truss design is a representative configuration design task, and the results can translate to other configuration design problems [26,39].

To design a truss, designers utilize a sequential design process of building a truss structure to support loads given anchor nodes. Figure 2 shows the truss design problem used in this PSADA

Table 1 PSADA model design parameters for the truss and UAV design implementations

Parameter	Truss implementation	UAV implementation	Notes
Initial temperature (T_i)	0.1	2000	Dependent on objective function, Empirically informed
Cooling constants (c_p)	High proficiency: 0.99 Med proficiency: 0.95 Low proficiency: 0.90	High proficiency: 0.99 Low proficiency: 0.90	Determines design space search strategy, Empirically informed
Action selection	Hidden Markov model for each proficiency level	Hidden Markov model for each proficiency level	Determines move selection heuristics, Empirically derived
Sharing probability	See Eq. (3)	N/A, Team design not tested	Step function, Empirically informed
Switching probability	See Eq. (5): $\beta_1 = 0.74$ $\beta_2 = 0.42$	N/A, Team design not tested	Logistic regression, Empirically derived

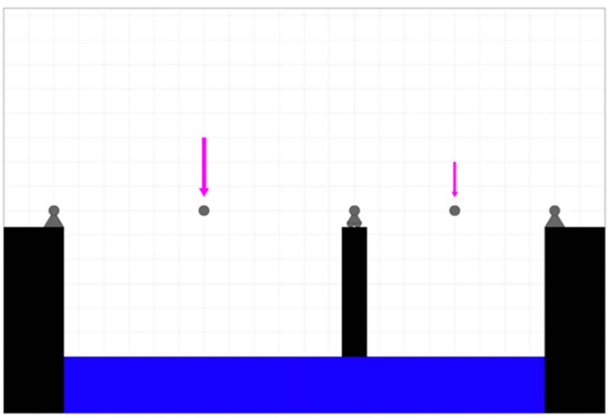

Fig. 2 Truss design problem that is used. The three anchor nodes and two load-bearing nodes are immovable. The arrows represent a load in the direction the arrow is pointed and the length of the arrow represents the relative load size.

work. This problem represents a familiar yet non-trivial problem to mechanical engineers. Any two-dimensional truss problem can be used in the PSADA model.

Every truss design problem begins with building the initial topology of the truss design by adding nodes and members until the truss design is stable and statically determinant so that it can be evaluated. In PSADA, a truss design is instantiated by adding nodes and members sequentially until a stable and statically determinant truss design is reached. Upon instantiation, agents can take one of seven actions at each step in the sequential design process. Table 2 shows the possible actions, along with a brief description of each. This set of actions mimics that of the human subject study. The designers in the human subject study were asked to "design a truss to meet a goal factor of safety (FOS) = 1.25, with as low of a mass (m) as possible." An objective function is developed for use in PSADA to be consistent with the stated objective for the human subject study, as shown by Eq. (6). The objective function is

$$q = \begin{cases} \left(\frac{m_{\mathrm{t}}}{m_{\mathrm{a}}}\right)\left(\frac{\mathrm{FOS_a}}{\mathrm{FOS_t}}\right), & \mathrm{FOS} < 1.25 \\ \left(\frac{m_{\mathrm{t}}}{m_{\mathrm{a}}}\right) & \text{otherwise} \end{cases} \tag{6}$$

In Eq. (6), q is the quality of the solution, m_{t} is the target mass based on the specific truss problem, m_{a} is the mass of the current truss, $\mathrm{FOS_t}$ is the target factor of safety, which is always 1.25, and $\mathrm{FOS_a}$ is the lowest factor of safety for any single truss member. This objective function is the truss's strength-to-weight ratio (SWR).

3.2 Unmanned Aerial Vehicle Design.

HyForm is a platform that was developed to study hybrid teams. This platform includes an unmanned aerial vehicle (UAV) design interface, shown in Fig. 3. UAV design in the HyForm platform is a configuration design problem, where the UAVs are comprised of motor–rotor pairs, battery structures, and foils connected in a grid. Designers can construct a UAV and simulate its validity and performance [40]. Table 3 shows the possible actions, along with a brief description of their UAV PSADA implementation.

An experiment by Zhang et al. published data for individual designers ($n = 20$) building drones to meet specific objectives [41]. These data on individual designer behavior and performance are used to extract move selection heuristics via HMMs for different

Table 2 Actions and action descriptions for truss design

Action name	Action description
1. Add node and attach	Adds a node to the design space and attaches it to the three nearest nodes with members. This ensures that the truss design is stable and statically determinant to evaluate the FOS of the design.
2. Add member	Adds a member between the two nearest unconnected nodes in the design space.
3. Delete node	Probabilistically selects and deletes a node from the design space and all members attached to it. The probability is proportional to the sum of the factors of safety of each member attached to the joint.
4. Delete member	Probabilistically selects and deletes a single member from the design space. The probability is proportional to the factor of safety of the member.
5. Resize all members	If a majority of members have a factor of safety below the target factor of safety, all members are increased in size. Otherwise, all members are decreased in size.
6. Resize single member	Probabilistically selects a member with probability proportional to $\lvert \mathrm{FOS} - \mathrm{FOS_{target}} \rvert$. If at least one member is failing, only members that are failing can be selected. Once a member is selected, if $\mathrm{FOS} > \mathrm{FOS_{target}}$ the size is decreased, otherwise it is increased.
7. Move node	Randomly selects a node in the design space and moves it. After a node is selected a direction is randomly chosen and a distance is chosen from a set of five predefined distances.

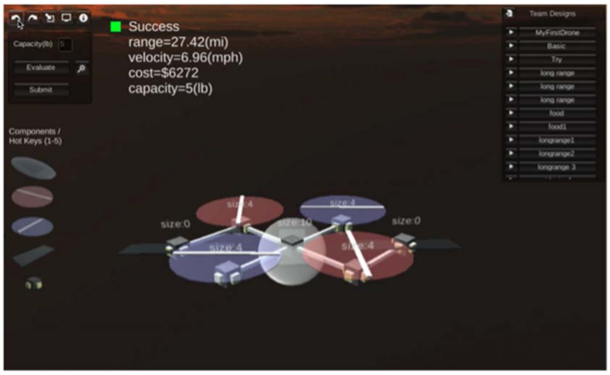

Fig. 3 HyForm UAV design platform with sample UAV

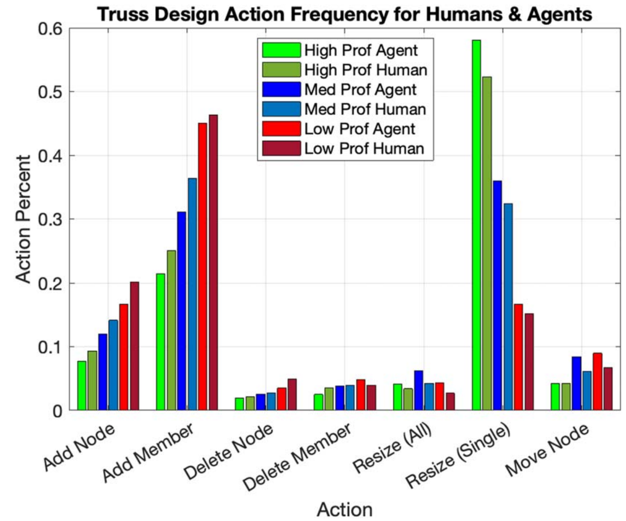

Fig. 4 Move frequencies for human designers and PSADA model agents separated by proficiency for the truss design problem

proficiency drone designers to build PSADA model agents for UAV design. The first set of objectives for the human subject study was to "construct a fleet of UAVs that [are]: (1) Capable of flying a total distance of 20 miles and (2) capable of flying a total distance of 50 miles." The objective function for the UAV design problem is, therefore, simply the distance that the UAV can travel.

Two significant groupings are found in this dataset of human designer performance. Therefore, no medium proficiency designers were categorized in this dataset. Human designers are categorized into high- and low-proficiency designers. HMMs are derived from the action sequences of these high- and low-proficiency designers.

4 Results

The results aim to validate the model of engineering proficiency proposed in Sec. 2. This is done by comparing results from the computational model with the previously conducted human subject studies. The only parameters that change across design tasks or for different levels of proficiency are those that are summarized in Table 1.

4.1 Individual Agent Validation. Proficiency is inherently an individual characteristic. Therefore, the proficiency of individual agents must be validated before they are put into teams. The human subjects designed trusses and UAVs in the same scenarios as the agents, which enables a comparison of PSADA and human designers. As discussed in Secs. 3.1 and 3.2, the human data from the truss design task had three distinct proficiency levels, and the human data from the UAV design task had two distinct proficiency levels. Therefore, the PSADA model implementation has high-, medium-, and low-proficiency agents for the truss design task and high- and low-proficiency agents for the UAV design task. One hundred individual PSADA model agents of each proficiency level are instantiated, and their results are analyzed.

As a reminder, the PSADA model aims to model characteristics of designers with different proficiency levels to create agents that mimic human designer behavior and performance. In other words, the agents' behavior should match that of human designers with the expectation that if the agents *behave* like various proficiency designers, they will *perform* like various proficiency designers.

Therefore, the behavior of PSADA model agents is compared to human designers on the two design problems first. Figures 4 and 5 show the action frequency of the different proficiency agents and the different proficiency designers in the truss and UAV design problems, respectively. The different proficiency human designers exhibit different action frequencies, and move selection heuristics that are modeled in PSADA are able to capture these differences for both the truss and UAV design problems. By visual inspection, the different proficiency agents select actions with similar probabilities to the corresponding proficiency human designers. In the truss design problem, the KL divergence for each proficiency pairing (high–high KL: 0.0128, medium–medium KL: 0.0180, low–low KL: 0.0157) confirms that the distributions are closer than each proficiency non-pair (high agent–medium human KL: 0.1543, medium agent–high human KL: 0.0625, low agent–medium human KL: 0.0633). For succinctness, the KL divergence for the furthest apart distributions is not included. The same is true for the UAV design problem (high–high KL: 0.0050, high agent–low human KL: 0.0739, low–low KL: 0.0073, low agent–high human KL: 0.0646).

The design space search strategy is the other behavior that is explicitly modeled in PSADA. In the original human subject

Table 3 Actions and action descriptions for UAV design

Action name	Action description
1. Add motor–rotor	Add a motor–rotor to empty grid location. Place *x*- and *y*-axis symmetric motors to maintain balance.
2. Add foil	Add a foil to an empty grid location. If $x = y$, place 1 additional foil at $-x$, $-y$ to maintain balance. If $x \neq y$, place three additional *x*- and *y*-axis symmetric foils to maintain balance.
3. Add battery structure	Add a structure to an empty grid location. If $x = y$, place 1 additional structure at $-x$, $-y$ to maintain balance. If $x \neq y$, place three additional *x*- and *y*-axis symmetric structures to maintain balance.
4. Delete motor–rotor	Randomly select and delete a motor-rotor and the *x*- and *y*-axis symmetric counterparts.
5. Delete foil	Randomly select and delete a foil and the *x*- and *y*-axis symmetric counterparts.
6. Delete battery structure	Randomly select and delete a structure and the *x*- and *y*-axis symmetric counterparts.
7. Resize motor–rotor	Randomly select and resize a motor–rotor and the *x*- and *y*-axis symmetric counterparts.
8. Resize foil	Randomly select and resize a foil and the *x*- and *y*-axis symmetric counterparts.
9. Resize battery structure	Randomly select and resize a structure and the *x*- and *y*-axis symmetric counterparts.
10. Switch design	Switch to a previously saved UAV. After a better UAV is found, agents have a small probability to save their current design.

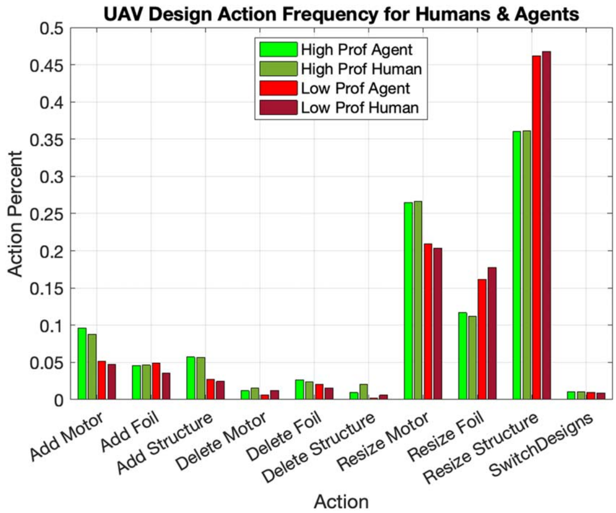

Fig. 5 Move frequencies for human designers and PSADA model agents separated by proficiency for the UAV design problem

study, it was discovered that low-proficiency designers spent longer exploring the design space before selecting a design topology and refining it. This was uncovered by analyzing the designs being created, including the number of topology elements in the designs. For truss design, the topology elements are the nodes and the members of the truss. Figure 6 replicates this analysis for the PSADA model agents and compares the results to the human designers. Because the design space search differs for different design problems, the equivalent analysis does not hold the same meaning for the UAV design problem. The topology of a UAV interacts differently for a UAV design problem. The number of topology elements for low- and high-proficiency designers were compared and 300 two-sample *t*-tests resulted in zero significant differences for this analysis. Thus, the comparison between human and agent designers was not conducted.

Figure 6(*a*) shows that the truss designs that are created by the different proficiency agents replicate the results from the different proficiency human designers (Fig. 6(*b*)). In both cases, all designers add topology elements to their design until approximately action 20, which is the required number of actions required to create the most common truss topology for the design scenario that is used. After building the initial truss topology, higher proficiency human designers and PSADA model agents do not add as many topology elements during the remainder of the design session. Low-proficiency human and agent designers, however, continue to add topology elements to their truss designs.

The different proficiency PSADA model agents were compared to their respective proficiency level human designers using two-sample *t*-tests. Only the iterations after the 20th action were compared. In total 204 two-sample *t*-tests were conducted and thus, the Holm–Bonferroni correction is used to set the significance levels. Of the 204 tests, only 11 of them yielded significant results. The tests for the high proficiency designers in action numbers 21–27 ($p<0.00026$) account for seven of the significant differences. After this initial difference, the high-proficiency human and agent designed trusses do not have a statistically different number of topology elements. The final four iterations ($p<0.00091$) for the low-proficiency designers yielded statistically significant results. In general, these results demonstrate that the agents are not designing trusses that are significantly different from the human designers and that all proficiency level agents are exhibiting the appropriate search behavior.

Upon validating the behavior, the averaged performances of the different proficiency human designers versus the averaged performance of the different proficiency PSADA model agents are compared and shown in Figs. 7 and 8 for both design problems. For the truss problem in Fig. 7, all agents and human designers have a mean quality of their first stable and statically determinant truss slightly below 0.3. The final values of each level of proficiency are consistent between the two as well. Beyond the initial and final quality, the trends for all three proficiency levels are reproduced by the PSADA model, with some minor exceptions. For each iteration, a two-sample *t*-test is conducted between the mean truss quality for the high, medium, and low proficiency PSADA agents and human designer pairings. One hundred and fifty-four significance tests are conducted, and the Bonferroni correction is used to set the significance level. For the high-proficiency and medium-proficiency designer and agent pairings, the tests failed to find a significant difference between the means of the two populations at any iteration. For the low-proficiency designer and agent pairings, only iterations 9, 12, and 15 resulted in statistically significant differences.

For the UAV design problem in Fig. 8, all human designers and agents are given a starting basic UAV design, and therefore all had a minimum best UAV range of ∼10. Early in the design session, the

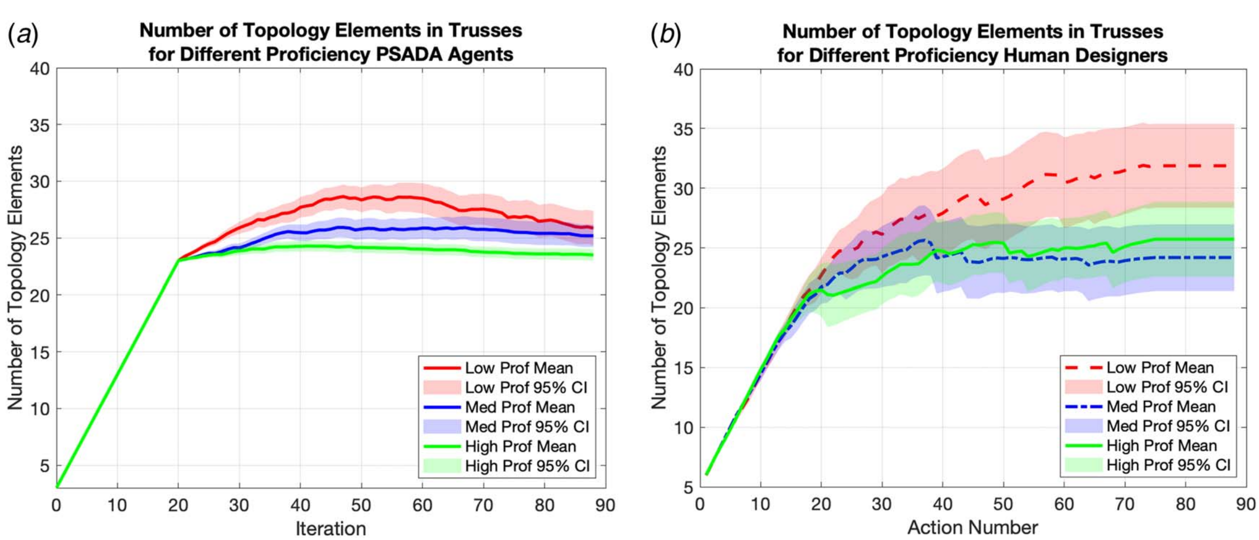

Fig. 6 The number of topological elements (truss nodes and members) in the trusses that are being designed by different proficiency (*a*) PSADA model agents and (*b*) human designers. For both humans and computational agents, the low-proficiency designers create more topologically complex trusses.

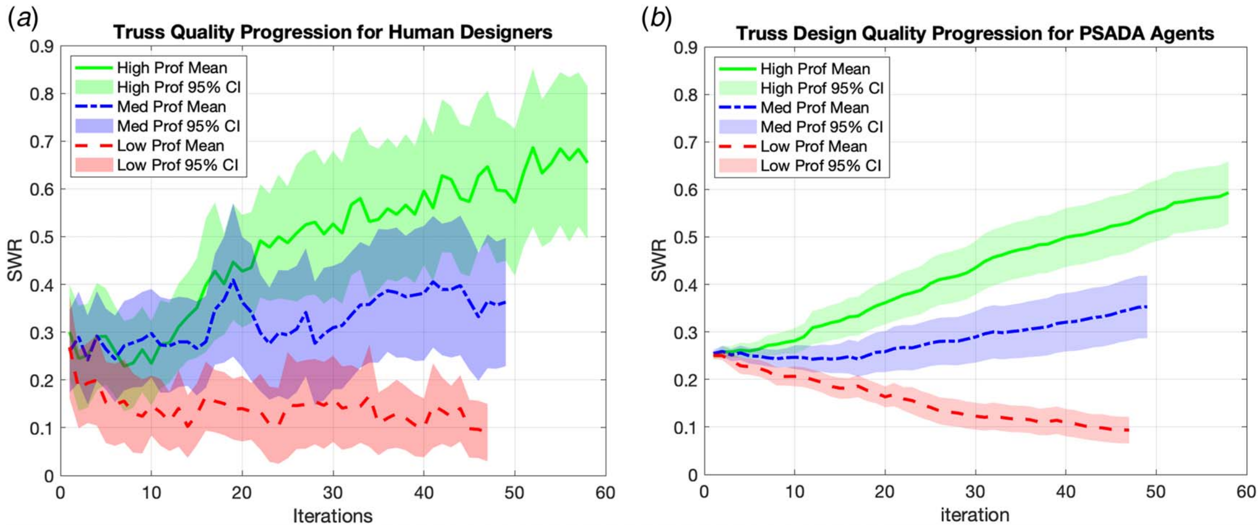

Fig. 7 Truss design quality progression by iteration for (*a*) human subject designers and (*b*) PSADA model agents. Shaded areas in the plots represent the 95% confidence interval for the mean of each condition.

average design quality is not significantly different between the high- and low-proficiency human designers or agents when using a two-sample *t*-test at a $p < 0.01$ significance level. A stricter significance level was used due to the high number of significance tests being conducted. Only after the 224th action for the human designers ($p = 0.00180$) and the 228th action for the agents ($p = 0.00979$) do the high-proficiency designers have significantly better designs on average than their lower-proficiency counterparts. The average design quality is never significantly different when comparing the low-proficiency human designers and agents. However, the difference between the design quality for high-proficiency designers and agents is significant late in the design session. The human designers achieved a significantly better UAV quality after the 237th iteration. Despite the difference between high-proficiency agents and human designers, there is still a significant difference between low- and high-proficiency agents.

Although many of the high-proficiency agents achieve high ranges for their UAVs, which is defined as a range > 50 (the high proficiency human designer range criteria), not all are able to achieve this. The UAV design problem has a complex design space with large areas of unstable UAVs with an objective function value of zero. Some agents get trapped and spend long periods in zero-quality design space areas, limiting their ability to produce high-quality designs. The model is built first to mimic the human designer's behavior and then to determine whether the behavioral differences modeled between different proficiency designers can account for the differences in performance. Ultimately, the PSADA agents are not able to escape these zero-quality regions in the same way as the human designers for this single proficiency level.

Another limiting factor for the UAV design problem agents from mimicking the high-proficiency human designer performance is the limited number of high-proficiency human designers. While there are enough designers to optimize HMMs for high- and low-proficiency agents, the HMMs would improve with additional human subjects. Because the dataset is from published data instead of the author's work, additional data are unavailable. Despite these issues, the PSADA model can still produce high-proficiency agents with significantly better-quality UAVs than their low-proficiency counterparts.

While Figs. 4–8 demonstrate the validity of the PSADA model in two different design scenarios, it is also important to demonstrate that the individual characteristics that are modeling proficiency—design space search strategy and move selection heuristics—contribute to these results. To test this, each characteristic is "turned

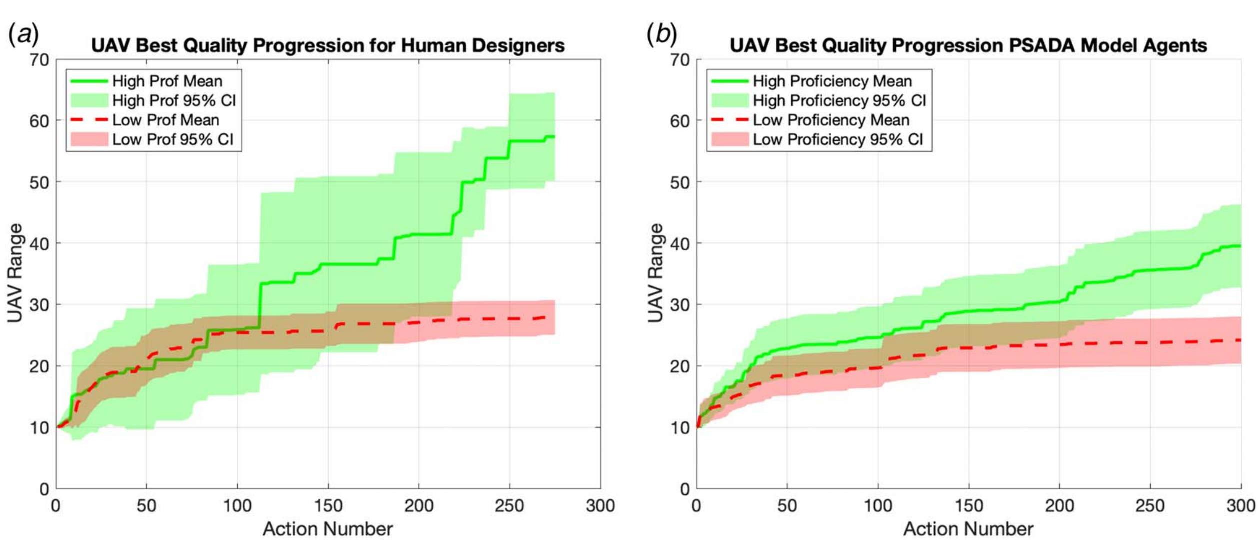

Fig. 8 UAV design quality progression by iteration for (*a*) human subject designers and (*b*) PSADA model agents. Shaded areas in the plots represent the 95% confidence interval for the mean of each condition.

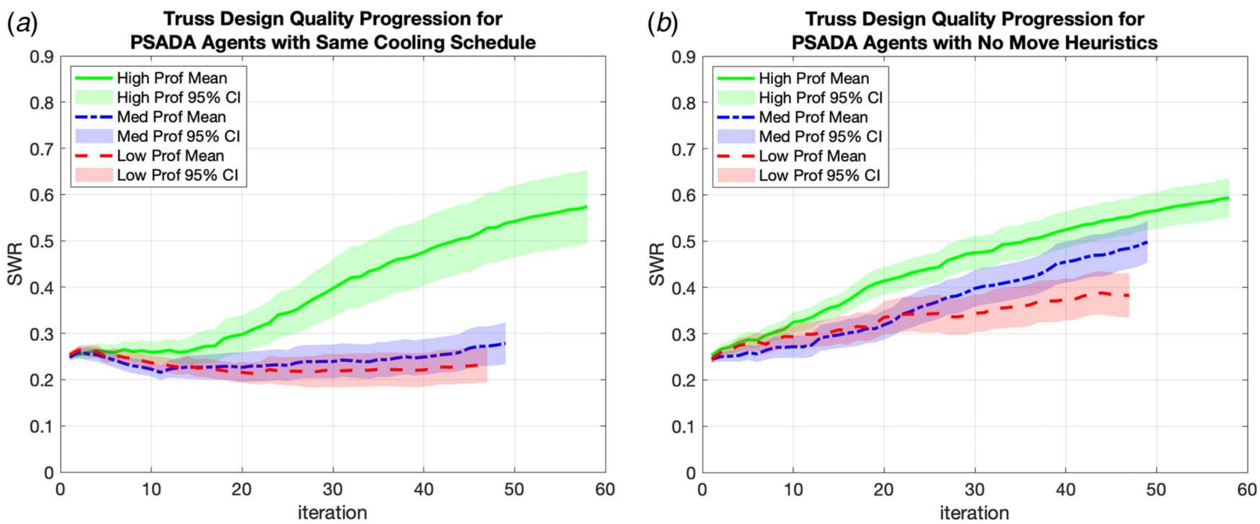

Fig. 9 Design quality progression for modified PSADA agents with (*a*) design space search strategy characteristic "turned off" and (*b*) move selection heuristics characteristic "turned off." Shaded areas in the plots represent the 95% confidence interval for the 95% confidence interval for the mean of each condition.

off," one at a time, so the modified PSADA model can run without the characteristic to show how the results change. The results of this experiment with the truss design problem are in Fig. 9.

The design space search strategy characteristic determines the cooling constant, c_p in Eq. (2), for each level of proficiency. To "turn off" this characteristic, each proficiency level is given the same cooling constant. In the test, each is given a cooling constant of 0.95. The rest of the PSADA model remains unchanged (i.e., the different proficiency agents still had unique HHMs) during this test, and 100 instances of the modified model are run with individual agents. Figure 9(*a*) shows the results of this test.

The move selection heuristics use HMMs to probabilistically choose an action at every iteration. Each level of proficiency has a different HMM derived from human data. To "turn off" move selection heuristics, each level of proficiency selects a random action at every iteration instead of choosing an action based on the HMMs. The rest of the model remains unchanged (i.e., each proficiency level had a unique c_p) during this test, and again 100 instances of the modified model are run with individual agents. Figure 9(*b*) shows the results of this test.

As Fig. 9 shows that both characteristics significantly impact the design quality progression for all proficiency levels when compared to Fig. 7(*b*). When both characteristics are used, PSADA agents closely follow human designers' behavior and performance trends. When one of the characteristics is not modeled, the performance differences are not fully captured. These results demonstrate that the characteristics modeled in PSADA capture the behavioral and performance differences between the different proficiency human designers in configuration design tasks.

4.2 The Relative Contribution of Different Proficiency Designers in Configuration Design Teams. The previous human subject study found that the most proficient team member of a configuration design team had the largest effect, positive or negative, on team performance. To validate this result, the team design portion of the truss design human subject study is reproduced using PSADA model agents. In the study, designers completed an assessment to determine their proficiency in truss design and then were placed into teams of three to design a truss collectively. The analysis is done with a multiple regression model. A nearly identical model is used to replicate this study with PSADA agents, as shown in Eq. (7). To test the effect of individual team member proficiency on team performance, the model

$$q_i = \beta_0 + \beta_1 m_{1,i} + \beta_2 m_{2,i} + \beta_3 m_{3,i}, \quad \forall\, i \in \mathbf{S} \tag{7}$$

is used, where $\mathbf{S}$ denotes the set of teams, $m_{1,i}$ is the teams' lowest proficiency members' proficiency score, $m_{2,i}$ is the teams' middle proficiency members' proficiency score, and $m_{3,i}$ is the teams' highest proficiency members' proficiency score. In general, $m_{n,i}$ will represent the team's nth least proficient member's proficiency score. The βs are the unknown coefficients and q_i is the teams' final truss quality. The proficiency score for each group of agents is the final mean quality when designing individually, which is shown in Fig. 7(*b*). This ensures that the relative quality of the different proficiency levels is accounted for in the regression model.

With three different proficiency agents modeled in PSADA, 10 different team configurations are possible for a team of three agents, one with three low proficiency agents, one with two low and one medium proficiency agents, one with two low and one high proficiency agents, etc. Each condition is run for 250 instances, and each team acts for 70 iterations. The results are shown in Fig. 10. The coefficient estimates for β_1 (the effect size of the lowest proficiency team member), β_2 (the effect size of the medium proficiency team member), and β_3 (the effect size of the highest proficiency team member), as shown in Fig. 10(*b*) show that improving any member of the design team will result in a positive effect on team performance. This result fits the logic that better team members will lead to better team performance. What is not as predictable is that raising the proficiency of the most proficient member has the largest effect on team performance. Therefore, the computational study with PSADA agents confirms the results from the previous human subject study that improving the highest proficiency member of a configuration design team will have the largest positive effect on team performance. This also validates the team characteristics of the PSADA model. With Welch's t-test, this result is statistically significant when comparing β_1 (lowest proficiency team member) and β_3 (highest proficiency team member) ($p = .0108$). However, the differences in effect size are not statistically significant when comparing β_2 (medium proficiency team member) and β_3 (highest proficiency team member) ($p = .7793$) or comparing β_1 (lowest proficiency team member) and β_2 (medium proficiency team member) ($p = .0757$). The general trend shows that the more proficient a team member is relative to their teammates, the larger their effect on team performance.

5 Conclusions

A computational model of configuration design proficiency is introduced in this work. The Proficient Simulated Annealing

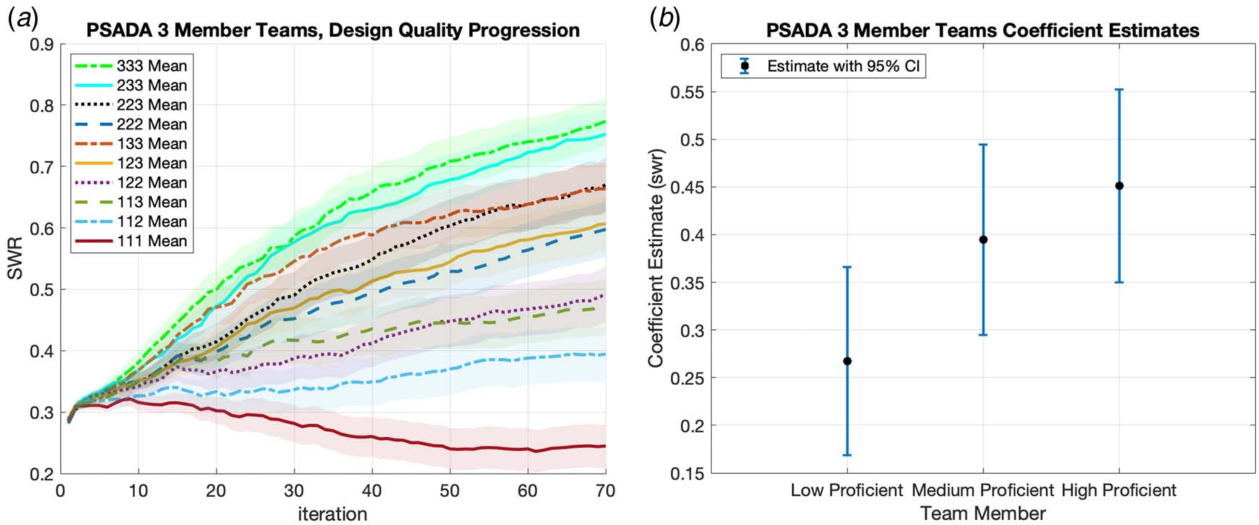

Fig. 10 (*a*) SWR Progression for each team condition throughout the design session. In the legend, low proficiency is represented by "1," medium proficiency is represented by "2," and high proficiency is represented by "3." (*b*) Coefficient estimates for Eq. (5), with 95% confidence intervals.

Design Agents model is shown to accurately model the behavior of human designers in two different configuration design problems. Additionally, the differences in behavior lead to significantly different performance levels, mimicking human performance with just one exception. In a truss design problem, three proficiency levels are validated against human subjects from a previously conducted human subject experiment. In a UAV design problem, two proficiency levels are modeled and compared to human subjects' behavior and performance. The behaviors of action selection and design space search are accurately modeled in both problems. The performance of all three proficiency levels in a truss design problem is accurately matched. The performance of the low-proficiency designers accurately matches the UAV design problem. The high-proficiency agents perform significantly better than the low-proficiency agents but do not mimic the performance of their human-designer counterparts. The reason for this difference in performance is discussed.

Upon validation, PSADA agents can be placed into teams to collaboratively design configurations with the same effect as their human counterparts. For the truss design, it is confirmed that the highest proficiency team member has the largest effect on team performance. This shows the PSADA model's ability to computationally model certain engineering design teams. In this introduction to the PSADA model, individual proficiency in configuration design problems is studied. However, now that the model has been validated to mimic human designers of different proficiency levels and design teams, PSADA can be utilized in future experiments to test other characteristics, other engineering design tasks, other team structures, and engineering design organizations that distribute designers to multiple teams simultaneously.

PSADA allows for an in-depth analysis of designer proficiency's role in configuration design teams. With this model, it can be confirmed that the previously discovered behavior differences between various proficiency designers account for a large portion of the variance between different proficiency human designers in engineering configuration design. The PSADA model does not currently model other characteristics that interact with proficiency. Personality, operational learning, and leadership could affect how low-proficiency designers learn during a design session to become higher-proficiency designers and how they use their knowledge and expertise to influence lower-proficiency teammates positively. Incorporating new cognitive and behavioral characteristics into the PSADA structure is possible and is a fruitful area for future work. Additionally, the PSADA model requires human data for the move selection heuristics. Without a previously conducted human subject study to train HHMs for different proficiency agents, applying the PSADA model to new design tasks would not be possible.

It is impractical to assume that every designer will be of the highest proficiency and that understanding how best to utilize people of different proficiencies can lead to better outcomes. This work shows that the PSADA model is a foundation for a deeper understanding of the role that individual team member proficiency plays in engineering design teams, yielding novel insights into this area.

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Conflict of Interest

There are no conflicts of interest.

Data Availability Statement

The datasets generated and supporting the findings of this article are obtainable from the corresponding author upon reasonable request.

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