Improving Human Situation Awareness in AI-Advised Decision Making

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***Abstract*—Human-autonomy teams aim to leverage the different strengths of humans and autonomous systems respectively to exceed the individual capabilities of each through collaboration. Highly effective human teams develop and utilize a shared mental model (SMM): a synchronized understanding of the external world and of the tasks, responsibilities, capabilities, and limits of each team member. Recent works assert that the same should apply to human-autonomy teams; however, contemporary AI commonly consists of "black box" systems, whose internal processes can not easily be viewed or interpreted. Users can easily develop inaccurate mental models of such systems, impeding SMM development and thus team performance.**

We seek ways to support the human's side of Human-AI SMMs in the context of AI-advised Decision Making, a form of teaming in which an AI suggests a solution to a human operator, who is responsible for the final decision. This work focuses on improving shared situation awareness by providing more context to the AI's internal processing. We hypothesize that this will lead the human to a more accurate mental model of the task and the AI, which in turn will improve team performance. We manipulate the human's situation awareness of the task environment and measure effects on the shared mental model. A between-subjects, randomized experiment is conducted in which participants in 6 treatment groups of varying amounts of contextual information (as a proxy for situation awareness) complete a task with an AI teammate. We find that improving shared situation awareness of decision points improves the human's overall performance, as well as their understanding of their AI teammate, without directly explaining the AI's internal mechanisms. Additionally, we find that increasing the human's situation awareness of task environment and AI teammate reduces over-reliance on the automated teammate.

***Index Terms*—shared mental models, shared situation awareness, human autonomy teaming**

I. Introduction

In human-AI teaming, humans are paired with artificially intelligent "partners" with the goal of leveraging the complementary strengths of each to improve task performance. However, critical problems arise when partnering with so-called "black box" systems - those whose decision-making processes are not easily interpretable by humans [1] - namely, that it is difficult or impossible to recognize erroneous output, or to know how to fix such errors. Black boxes are particularly common in recommender systems where the model or algorithms underlying the artificial intelligence (AI) is often hidden from the human teammate [2], [3].

The field of explainable AI (XAI) aims to address this barrier by providing explanations of a system. The most common types of explanation are global explanations, which explain the behavior of the model as a whole, and local explanations, which offer a specific explanation for that specific set of decision parameters. An example of a global explanation would be a full set of heuristics or rules used to classify inputs into outputs, while a local explanation might offer a specific rule or set of rules used to map the input to output [4]–[6].

Both approaches are under active study and carry limitations. Explanations can take many forms [5], and there is no consensus on what qualifies as a good or effective explanation. For some AI algorithms, explanations can be straightforward, such as displaying a decision tree or providing the features that triggered the decision. For other algorithms, such as deep neural networks, the sheer volume of parameters and nodes used by the algorithm makes extracting a straightforward human-like explanation from them very difficult. Additionally, the explanation given to the human is only useful if it is relevant to their existing mental models, and only if it succeeds at increasing the human's understanding. The given explanation needs to be communicated at a level of abstraction that makes sense to the individual user.

In joint human-AI decision making tasks, utilizing a black box AI can lead to satisfactory results if the decision problem is well-characterized and simple, or if the human is an expert in the task. However, this black box approach may fail in more complex settings. In these cases, when the result of the decision is unsatisfactory, or at worst, catastrophic, there are no mechanisms or structures in place to understand why that decision was made. Since algorithmic transparency is necessarily limited, we turn instead to naturalistic decision making (NDM) literature, which considers the decision event itself less important than the perception and judgment efforts leading up to the decision, and to shared mental model (SMM) theory. The team's SMM is a representation shared by all teammates of the task at hand and the roles, responsibilities, and capabilities of each teammate. Part of this includes having shared situation awareness (SSA) which can be defined as "a shared understanding of that subset of information that

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is necessary for [every teammate's] goals" [7]. We propose bolstering the human's mental model of their AI partner by supporting their cognitive process of judgment/orientation in the decision making process. We hypothesize that providing judgment support in this way will improve SSA between the teammates, which in turn will impact overall performance.

II. Background

A. Shared Mental Models

Mental models [8] are internal representations of how and why a phenomenon occurs. People create mental models of complex systems as a part of interacting with them [9]. Following from this is the concept of *shared* mental models [10]: mental models that are held in common across multiple individuals that serve to support a shared task. The key finding from SMM literature is that if human teammates have similar mental models of their shared task and of each other, then they are able to accurately predict their teammates' needs and behaviors. SMMs enable high-performing teams in which everyone understands and anticipates the work of others in the team. Teammates make decisions based on a common understanding of the state of the world which affects team performance.

Some work has applied this concept analogously to human-AI teams, seeking to foster mutual task-and-teammate understanding between a human and an AI [11]. Work to improve the human's mental model of the AI [12] and vice versa [13] is ongoing, yet there are few empirical studies that attempt to quantify the development and effects of SMMs on human-autonomy teams. An exception is Hanna and Richards' study which directly correlates the effects of trust and commitment to SMM development in teams of humans and intelligent virtual agents (IVAs) [14]. Better shared mental models are found to positively correlate with human trust in their artificial teammate. Teammate trust is also found to significantly correlate with task commitment, which is found to significantly correlate with improved team performance. However, these measurements were made via subjective self-assessments of SMM quality. Indeed, because of the difficulty of eliciting and measuring a human-AI SMM, little research on this front has attempted to establish objective, quantitative links.

B. AI Driven Recommender Systems

Decision Support Systems (DSS) are a common application of AI in various industries. They are designed to assist operators in decision making tasks by either simplifying the decision space or generating potential solutions to reduce the burden on human decision-makers. Recommender systems are a subset of DSS in which the AI recommends a coarse of action for some decision that needs to be made. The process of decision making has been modeled in several ways [15]–[17], but for the purposes of this paper, we will focus on the well-known OODA loop [18] which models the following cognitive processes:

- Observation: the collection of data through sensory perception
- Orientation: the analysis and synthesis of data to form one's current mental perspective
- Decision: the determination of a course of action based on one's current mental perspective
- Action: the physical playing-out of the decision

The field of naturalistic decision making (NDM) focuses on understanding, modeling, and improving how people make decisions and perform cognitively complex functions (such as observing and orienting) in demanding, real-world situations. Several works within NDM have shown that context and spending sufficient time and energy on the process of orienting or judging relevant information is influential to the decision part of the decision-making process [19]–[21].

In AI-advised decision making tasks, the AI is responsible for the Observing and Orienting parts of the loop, and can also be used in the Decision part: The AI gathers relevant information (Observe), and uses that information to generate possible solutions (Orient) or a judgement of the decision that needs to be made (Decide). The human's role is mainly that of a safety checkpoint; the final decision (Decide) and implementation (Act) is the operator's responsibility. However, a black box AI prevents appropriate understanding of what information the AI is observing, and how the AI orients that information to produce its outputs. Because the human is not present in the Observation and Orientation parts of the decision-making loop, this prevents a successful convergence of SSA and thus, the SMM.

III. Methodology

We conducted a between-subjects experiment in which participants were asked to complete a decision making task using an autonomous decision support system. We manipulated the participants' situation awareness of the task environment and measured effects on the shared mental model between participants and their AI partner and on the final task performance. Participants were recruited through an online recruitment platform (Prolific, www.prolific.co). The experiment was conducted online and collected data from 90 participants (20 male, 70 female, ages 18-65). Participants were assigned randomly to a treatment and the order of scenarios shown to participants was balanced.

A. Task Domain

Participants took the role of the commander of a craft in Mars orbit, charged with finalizing the entry, descent, and landing (EDL) trajectory of a probe to a landing site. They were aided by an AI Mission Computer that made a parallel evaluation of the proposed trajectory and offered agreement or disagreement with the participant's decision; the participant had the final call on whether to execute or abort the mission. There were no time constraints on the task. For control and reproducibility, though the system was presented to participants as "intelligent", its responses in each scenario were predetermined and fixed.

The task is outlined in Fig. 1. First, the team (human participant and AI Mission Computer) independently assessed

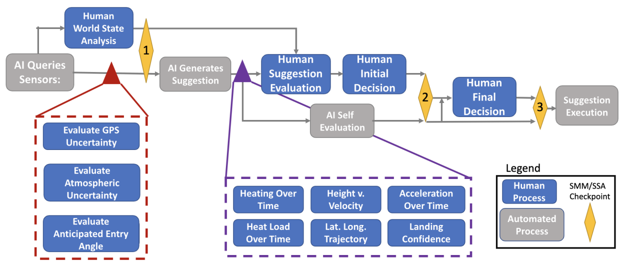

Fig. 1: Task Outline for EDL Trajectory Planning

the current state of the world, considering three factors: Orbital positions of GPS satellites, the locations of dust storms, and the atmospheric entry angle determined by the craft's current orbital state. The team evaluated whether the present world state permits a suitable landing (first decision point represented by the yellow diamond).

Then, the AI Mission Computer used the world state conditions to generate a possible trajectory for the probe's landing. The team was shown a set of six figures of merit that assessed the proposed flight plan: velocity vs. altitude; heating rate, heat load, and acceleration vs time; latitude vs. longitude; and landing confidence. These charts were shaded to indicate safe, risky, and dangerous thresholds, and the participants were instructed how to interpret each. Using the figures of merit, the team individually evaluated whether or not to execute the landing trajectory (second decision point represented by yellow diamond). The AI Mission Computer decision was made known to the participant after they had made their own. The participant made the final decision on whether to execute or abort the mission in light of the AI's recommendation (third decision point represented by yellow diamond).

B. Experiment Design and Task Procedure

The study included two independent variables: World State Awareness (3 levels) and Trajectory Awareness (2 levels). The study was designed as a 2x3 between subjects design. Participants were assigned to a single treatment which was a one of six combinations of the World State Awareness and Trajectory Awareness.

1) World State Awareness Assessment: For this independent variable the team separately evaluated how risky the world state was (risky conditions vs safe conditions) in that scenario. The World State Awareness variable had 3 levels: Observation-Only, Interactive, or Absent altogether. The Absent mode was our control group, and in it participants were not given any information about the world state. This lack of information mimics current black box systems, and participants started directly at the Trajectory Evaluation phase of the experiment. In the Observation-Only mode, participants viewed the three information screens. They were not prompted for any further engagement with the information. In the Interactive mode, participants viewed the world state information screens and were asked a multiple-choice question about each component, such as "Which satellite is closest to Mars?" and "How are the weather conditions near the landing zone?". These questions were intended to increase the participant's situation awareness by forcing them to actively process each information source to minimum degree.

After viewing and/or answering the question on each tab, participants were asked if the world state conditions were risky or safe enough to attempt a landing. The AI Mission Computer prepared its own answer to the same question. For implementation purposes, these responses were fixed *a priori*. The participant was then informed of the AI's judgment of the world state conditions (and thus whether they are in agreement). Then the trial proceeded to the next phase.

2) Trajectory Awareness Assessment: For this independent variable, a landing trajectory was presented and the team evaluated whether or not to execute it. Participants were shown a spread of six figures of merit that characterized the proposed flight plan. The Trajectory Awareness variable had 2 levels: Observation-Only or Interactive. In the Observation-Only mode, participants reviewed the six figures of merit for the AI-suggested trajectory and made an execute/abort decision. In Interactive mode, participants were additionally asked to mark each of the six figures of merit as "Good", "Bad", or "Maybe" according to that chart's specific risk factors. After observing (and possibly interacting with) each of the trajectory charts, participants were asked to decide to execute or abort the mission. As in the World State Evaluation step, the AI Mission Computer offered its own evaluation after participants gave their answer, and participants were asked again to make a final decision.

C. Experiment Procedure

Participants were asked to complete a consent form, given a pre-experiment questionnaire to establish their baseline trust in automation [22], and assigned to one of six experimental treatments. Instructional videos, tailored to each treatment, introduced participants to the task and the AI Mission Computer. No particular task-relevant experience was assumed. Participants completed six practice rounds of the mission planning task. They were required to meet a specific standard of performance in order to proceed past the practice rounds. Sufficiently performant participants proceeded to complete 10 trials of the mission planning task. Finally, participants completed two final questionnaires: 1) TLX workload [23] and 2) i-THAU trust assessment [22].

D. Experiment Considerations and Limitations

The "AI" behavior utilized in this version of the study is fully predetermined, with certain inputs (world state conditions) mapped to outputs (trajectory charts). To simplify analysis, the AI's suggestion is correct 100% of the time. This conflates team agreement with task performance, and as these two metrics are not realistically equivalent and 100% correct performance from AI is unlikely, future versions of the experiment will have less than ideal AI. Additionally, participants are assumed to have little to no experience in a Martian EDL mission planning task. In a real-world scenario, it is reasonable to expect that the human responsible for executing a mission of this nature would have moderate to expert experience and qualifications suited to this domain.

E. Measures

First, we recorded the agreement between the participant's and the AI's initial judgment of the world state conditions and between their initial decisions of whether or not to execute the proposed trajectory. This served as a crude measure of the final shared situation awareness (SSA) between the participant and the AI. If human and AI agree on their understanding of the world state (risky/safe) and agree on their initial judgement of what decision to take (abort/execute) then they have high SSA, since they have a highly shared understanding of the subset of information that is necessary for their goals. This was rolled up per participant basis across all 10 scenarios. Second, we recorded the final agreement state between the human and the AI after the AI's recommendation to execute/abort was revealed. Third, we recorded the number of decisions per participant that changed between initial and final decisions and from there computed the percentage of initial disagreements that were resolved. Fourth, for the interactive treatments, we checked that the understanding of the human matched the understanding of the AI.

Additionally, responses were recorded from the three subjective questionnaires. The pre-experiment questionnaire was an i-THAu trust assessment, in which participants rated a series of statements about their Faith in Persons and Faith in Technology on a seven-point Likert scale from [-3:3]. A composite average of their answers informs their overall dispositional trust in these two categories. The first post-experiment questionnaire was an unweighted NASA TLX workload assessment, which measured overall workload. The second was the remainder of the i-THAu trust assessment in which participants responded to a series of statements about their experience of working with the automated system, on the same Likert scale. For both i-THAu assessments, a rating of -3 indicated a lack of trust– the subject didn't trust people/technology or depend on the AI to help them with the EDL task, or they didn't understand the role of the AI. Conversely, a rating of 3 indicated high levels of trust, dependence, or understanding.

IV. Results

We first assessed the shared situation awareness of the two teammates (yellow diamond 2 in Fig 1). Figure 2 shows the percentage of the initial agreement between the participant and the AI during the World State Evaluation (WSE) and Trajectory Evaluation phases. Those who did not receive world state information tended to be in agreement with the AI Mission Computer 60% - 85% of the time. Once world state information was introduced, the participant and AI Mission Computer tended to agree 80% - 95% of the time, and the variation was reduced. This indicates that being aware of the decision environment (the world state conditions) increased the shared situation awareness about the specific decision task, i.e. trajectory evaluation.

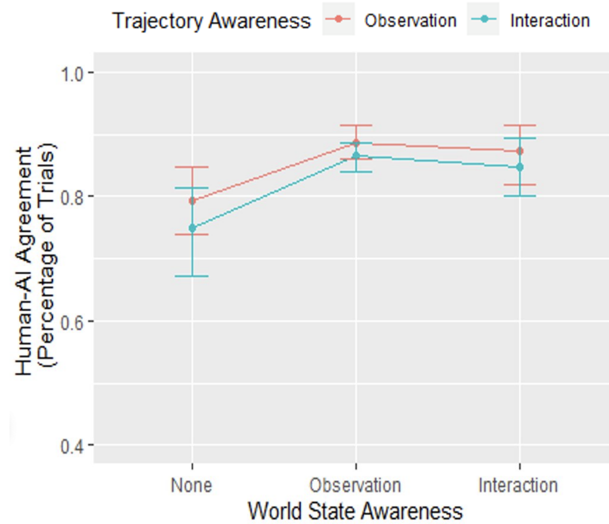

Fig. 2: Final Shared Situation Awareness [%] Between Human and AI During Evaluation Phases

TABLE I: ANOVA for Final SSA

	df, error	F	P
WSAwareness	2, 82	10.425	0.0001
TrajAwareness	1, 82	2.960	0.0891
Faith in Tech	1, 82	0.250	0.6181
Faith in Persons	1, 82	0.596	0.4424
WS-A:Traj-A	2, 82	0.650	0.5248

To determine the significance of the relationship, we performed a linear mixed effects analysis of the relationship between the initial decision agreement between the participant and the AI Mission Computer (before the AI's decision was revealed) and our independent variables. The fixed effects were the World State Awareness, Trajectory Awareness, the average dispositional trust in people and the average dispositional trust in technology. We also included an interaction effect between World State Awareness and Trajectory Awareness, and intercepts for subjects as a random effect. Table I presents the analysis of variance (ANOVA) for the fitted linear mixed-effects model. The results indicate that the World State Awareness is statistically significant in predicting the initial agreement between the participant and AI. No other effects were significant.

A well known challenge in human-automation/AI teams is that humans can often over rely on their computational teammates. Figure 3 shows the percentage of the team's final agreement after the AI reveals its decision and the participant makes the final call on whether to execute or abort the mission (shown as yellow diamond 3 in Fig 1). The average final agreement was approximately 90% for all levels of World State Awareness but the variance decreased as World State Awareness increased. We performed a linear mixed effects analysis of the relationship between the final decision agreement between the participant and the AI and the aforementioned independent variables. We then conducted

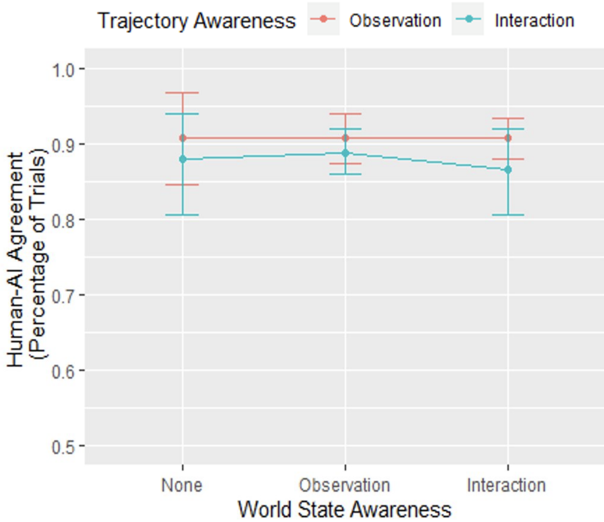

Fig. 3: Final Agreement [%] Between Human and AI

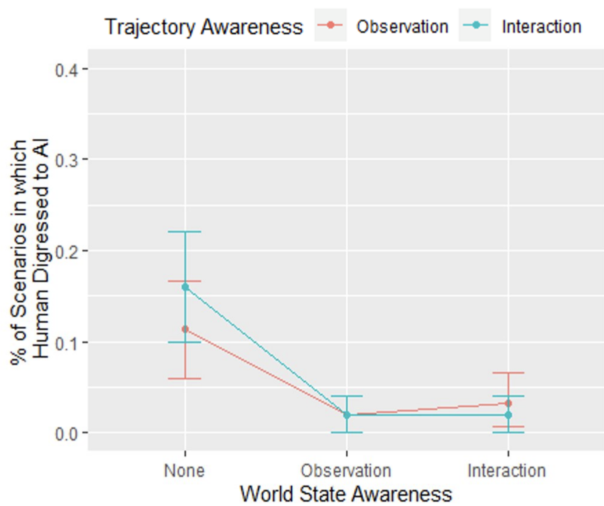

Fig. 4: Resolved Team Disagreements [%] Post-AI Suggestion

an ANOVA on this model (Table II). None of the fixed effects were statistically significant in predicting the final agreement between the team.

TABLE II: ANOVA for Final Agreement

	df, error	F	P
WSAwareness	2, 82	0.076	0.9265
TrajAwareness	1, 82	1.844	0.1782
Faith in Tech	1, 82	0.357	0.5518
Faith in Persons	1, 82	0.483	0.4888
WS-A:Traj-A	2, 82	0.030	0.9706

Looking at the data another way, Figure 4 depicts the percentage of times the participant reconsidered their initial decision to align with the AI after seeing what the AI suggested during the evaluation phases. We performed a linear mixed effects analysis of the relationship between this gap in agreement between the teammates and the aforementioned independent variables. We then conducted an ANOVA on this model (Table III). The results indicate that the World State Awareness is statistically significant in predicting when the participant will change their decision to align with the AI's suggestion. No other effects were significant. Based on Figures 3 and 4, we can see that those who did not have access to the world state conditions had a tendency to over-rely on their AI partner to make the correct decision, while those who did observe or interact with the world state conditions had higher initial agreement with the AI in the first place.

TABLE III: ANOVA for Resolved Team Disagreements

	df, error	F	P
WSAwareness	2, 82	18.95	<0.0001
TrajAwareness	1, 82	0.408	0.5244
Faith in Tech	1, 82	0.004	0.9508
Faith in Persons	1, 82	0.933	0.8565
WS-A:Traj-A	2, 82	1.183	0.3115

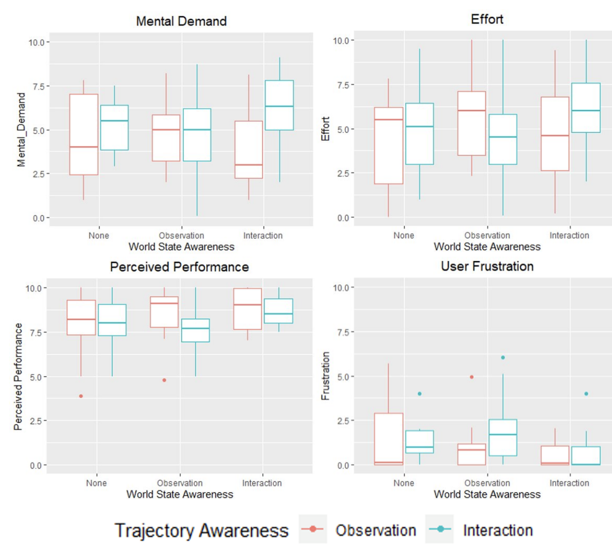

Fig. 5: Composite Results of NASA TLX Questionnaire

To determine if adding the extra tasks of allowing or requiring participants to be aware of the world state and trajectory assessments, we conducted a subjective mental workload assessment (NASA TLX) at the end of the experiment. Figure 5 depicts the results of the NASA TLX questionnaire. For all metrics except perceived performance, higher values indicate a higher workload on the participant. For perceived performance, higher values indicate a better perception of their own performance. Overall, increasing the participant's situation awareness required more effort of them but ultimately was less frustrating and resulted in increased perceived performance. Results also show that those who interacted with the figures of merit (as opposed to merely observing them) during the Trajectory Evaluation phase tended to experience more mental demand and frustration, and perceived themselves as less successful in their performance.

V. Discussion

The results of this study indicate that increasing the human's awareness of the task environment improves their agreement with their AI partner. Since agreeing with the AI was equivalent to performing correctly, this means that providing world state information increased shared situation awareness (Fig. 2) and improved team performance. Additionally, while the final agreement was around 90% for all levels of World State Awareness, the variance decreased as World State Awareness increased, indicating that more people tended to agree with the AI and perform successfully as their situation awareness increased. We also found that those who did not have access to the world state conditions had a tendency to over-rely on their AI partner to make the correct decision (Fig. 4). Additionally, the NASA TLX data indicate that, even if including the human in the Observation part of the decision making process required more effort on their part, it ultimately made their task less frustrating and raised their own confidence in their ability to perform the task. Based on these results, we can see that providing contextual information to the human and including them in the Observation stage of the decision making process can increase overall team performance and decrease over-reliance on automation without much added workload. This should generalize to any domain in which the decision maker is assisted by an AI that offers solutions, so that they have context for the solutions which helps the human's Orientation process.

In an effort to support the evaluation of a suggested course of action, we introduced an interaction component during the Trajectory Evaluation phase. However, we found that making sure humans understood the "goodness" of the suggestion did not improve their performance significantly nor did it improve shared situation awareness between the teammates which may contradict existing literature. In fact, we see from NASA TLX data that the interaction component tended to yield a worse user experience than merely observing the trajectory characteristics.

VI. Conclusions

This work is the first in a series of studies that will investigate different elements that can increase shared situation awareness and the effects SSA has within a human-AI mission planning system. This specific study varies the amount of interaction the human has with the task environment to increase the human's understanding of the task and their AI partner. Introducing transparency of the information that the AI uses to generate trajectories improves the shared situation awareness between the human and the AI (Fig. 2). While increasing transparency into the mission planning system by including the human in the observation part of the process increased the agreements between the human and AI (Fig. 2), improved human robustness to overreliance on automation (Fig. 4), and impacted the participants' experience (Fig. 5), there was no significant improvement in the final team performance (Fig. 3).

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