Learning with AI Assistance: A Path to Better Task Performance or Dependence?

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ABSTRACT

With the proliferation of AI, there is a growing concern regarding individuals becoming overly reliant on AI, leading to a decrease in intrinsic skills and autonomy. Assistive AI frameworks, on the other hand, also have the potential to improve human learning and performance by providing personalized learning experiences and real-time feedback. To study these opposing viewpoints on the consequences of AI assistance, we conducted a behavioral experiment using a dynamic decision-making game to assess how AI assistance impacts user performance, skill transfer, and cognitive engagement in task execution. Participants were assigned to one of four conditions that featured AI assistance at different time-points during the task. Our results suggest that AI assistance can improve immediate task performance without inducing human skill degradation or carryover effects in human learning. This observation has important implications for AI assistive frameworks as it suggests that there are classes of tasks in which assistance can be provided without risking the autonomy of the user. We discuss the possible reasons for this set of effects and explore their implications for future research directives.

CCS CONCEPTS

• **Computing methodologies** → Planning under uncertainty; • **Human-centered computing** → *Empirical studies in collaborative and social computing*; **Empirical studies in HCI**.

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KEYWORDS

AI-Assistance, Human-AI Interaction, Cognitive Offloading, Decision Making

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1 INTRODUCTION

In recent years, the technological landscape has witnessed a remarkable transformation with the widespread adoption of artificial intelligence (AI) systems across various sectors [10]. Once confined to specialized applications, AI now permeates daily life, powering smart devices and enjoying widespread adoption in industries like healthcare, education, and manufacturing [15] [9] [7]. From autonomous vehicles to voice assistants and text-based software, many believe AI's integration promises to enhance productivity by automating tasks, offering suggestions, and minimizing errors [18] [17] [1].

While the integration of AI technologies has the potential to provide significant benefits to humanity, care must be taken to ensure that the risk of adverse outcomes is mitigated. In the short term, AI technologies will likely be unable to replace all human economic functions [7]. This can be because the automation of some tasks are complex and nuanced. Alternatively, certain sectors may deem fully automatized systems as ethically impermissible. For example, fully autonomous vehicles are currently unavailable as consumer products and may remain so for the foreseeable future. This means that drivers of modern vehicles are being assisted by AI technologies more so than being replaced by them. Similarly, instances where legal decision-making has been replaced by autonomous solutions have received heavy criticism due to concerns around bias and lack of transparency [14].

One notable risk that has received extensive discussion is the potential for human task performance to become dependent on AI. Without intervention, dependence on AI could grow to the point where the absence of assistance would render the completion of task objectives virtually impossible [16] [22] [2]. Over-reliance may also lead to a decline in individuals' intrinsic skills and capabilities, as they increasingly defer decision-making and problem-solving to AI algorithms [5] [4] [3][23]. Moreover, continuous reliance on AI may result in reduced cognitive engagement with tasks, which may introduce externalities that render human-in-the-loop systems just as vulnerable to errors as fully automated systems [11]. Due to the increased scalability of automated decision-making relative to its human equivalent, these AI-enabled errors could be exponentially more catastrophic than the more limited scope of human errors. Consequently, the premature integration of AI assistance may lead individuals to experience a loss of autonomy and independence, diminishing their sense of agency and self-efficacy. Moreover, over-reliance on AI systems could add fragility to systems intended to have robust security assurances by preserving humans as contributors to decision-making. Thus, AI assistance must be designed with careful consideration of human affordances, such that the potential benefits of this assistance can be reaped while minimizing over-dependence risks.

A contrasting perspective to the notion of AI as a dependence-inducing technology is that AI can serve as an effective teacher and augment human learning and performance [20] [6] [13]. In this perspective, AI serves as a facilitator for enhancing individuals' understanding of tasks and improving their performance. By leveraging AI as a tool for guidance and instruction, individuals can benefit from personalized learning experiences tailored to their unique needs and preferences. AI can provide real-time feedback, offer insights into optimal problem-solving strategies, and present alternative approaches to task execution [19]. Moreover, AI-driven simulations and training modules could conceivably create immersive learning environments that allow individuals to practice and refine their skills in a safe and controlled setting [8]. By serving as a supportive mentor, AI can, and already does to some extent, empower individuals to acquire new knowledge, develop critical skills, and optimize their performance in various domains. Embracing AI as an effective teacher underscores its potential to transform human learning and performance, offering new avenues for skill acquisition, knowledge dissemination, and continuous improvement.

This paper presents an experimental investigation into the potential dual roles of AI as both a crutch and an effective teacher. By conducting a behavioral experiment, we aim to uncover the factors influencing individuals' reliance on AI, the cognitive processes involved in AI-assisted learning, and the implications for task performance and skill acquisition. Our findings will contribute to a deeper understanding of human-AI interaction dynamics and inform the design of AI systems that effectively support human cognition and performance.

2 EXPERIMENTS

2.1 Task

To study the effect of AI assistance on user performance, we constructed a challenging dynamic decision-making game where the player's goal is to maximize point gain by intercepting objects that are moving at constant speeds through a circular window (see Figure 1). The task shares some of the planning requirements of traveling salesman problems that have been studied in the context of human problem solving [12], but with the key difference that the objects in our task are not stationary and new objects constantly enter the scene, which requires online updating of the sequence of interceptions. Therefore, the task requires prioritization and planning not only to intercept a particular object but also to ensure the player is positioned well to intercept future high-value objects (which have either moved during the interception of the previous object or appeared on the screen) to maximize the total amount of points gained.

2.2 AI Assistance

We also designed an assistive AI agent that offers high-value action suggestions to participants during the task. The AI's suggestions are updated and displayed in real-time based on the player's current position as well as the current positions of the objects in view. AI assistance is provided in terms of a suggested location for the player to click next to intercept a particular object (see Figure 1, right panel for an example). Note that AI suggestions might not always prioritize intercepting the highest-value target. Instead, the AI plans and designs an interception sequence that is more likely to maximize the total value of objects intercepted over time (e.g. first intercept a lower-value object before it disappears from view as other higher-value targets can still be intercepted later).

2.3 Experimental Conditions

In the experiment, different groups of participants received AI assistance at varying points in the study. Specifically, we assigned each participant to one of four conditions. In condition A, participants were never provided AI assistance. In condition B, participants received AI assistance only in the first block of the experiment, after which participants performed the task without assistance. In condition C, we inverted this sequence such that participants in the first block had to perform the task without assistance, and AI assistance was provided in the second block. Finally, in condition D, AI assistance was always provided (see Table 1 for a summary of the design).

This design allowed us to test several hypotheses regarding the effect of AI assistance on learning. First, we can establish the extent to which performance improves when people are provided with AI assistance. As the AI planner could update its plans in real-time and plan interception sequences, we expect that AI assistance will improve participants' overall performance. Second, we can test how early learning with AI assistance affects later performance without AI. If learning a task with AI assistance leads people to offload all cognitive processing and planning to the AI, participants will not independently learn the task. In this case, the performance of participants in condition B is expected to decrease when AI assistance is turned off in the second block and becomes similar to the performance of participants in condition A who never learned with AI assistance (i.e., the performance in the second block of Condition B would be similar to the first block of Condition A). On the other hand, if the AI acts as an effective teacher, turning off AI

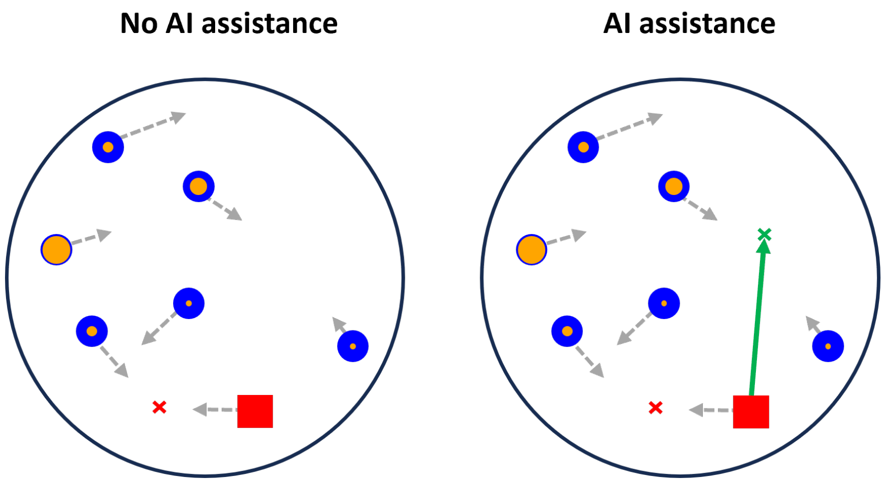

Figure 1: Illustration of the task across AI assistance conditions. Player and target motion paths are shown with gray arrows (not visible to participants) and AI-suggested paths (visible to participants) are shown in green. The red cross shows the location where the participant clicked. The orange fill indicates the value of a target. For visual clarity, the game is not drawn to scale.

assistance will put participants in a better position to independently perform the task relative to participants who never learned the task.

3 METHOD

3.1 Participants

189 participants were recruited through Prolific. Ages ranged from 18 to 73 (Mean = 37.19, SD = 11.75) with 55% female, 44% male, and 1% abstaining from this categorization. All participants were residents of the United States and had not participated in any of our previous pilot experiments. The study was conducted through the participant's personal computers. Each participant was compensated with 5 USD for a pre-allotted 30-minute time window. Since participants usually completed the experiment earlier than the 30-minute time window, participants were compensated at an average rate of 12.5 USD per hour.

Informed consent was obtained from each participant before beginning the study. The study protocols for all experiments were approved by the Institutional Review Board of the University of California, Irvine #4527, and the study was conducted in accordance with the principles of the Declaration of Helsinki. Confidentiality of responses was assured, and participants were informed of their right to withdraw from the study at any time without penalty.

3.2 Game Environment

The experiment involved an online game where the goal was to score as many points as possible by intercepting objects as they entered a circular area. The player's avatar is represented by a red square that can be moved within the confines of the circular area. The player's movement is controlled by clicking on a specific location on the screen, which directs the avatar in a straight path at a constant speed to that location. The game includes moving objects, represented as blue circles, that enter the play area at random points along the perimeter (see Figure 1 for examples). These objects move at a constant speed in a specific direction. Objects are initialized with moving speeds sampled from a uniform distribution that does not exceed the player's speed. When an object leaves the game area, a new object can be created. The spawning process is designed so that the number of objects in the game area is limited to the maximum number of targets. In this experiment, we limited the game to nine objects rendered in the game area. One key feature of the spawning process is that it is independent of the player's skill in interception. After a player intercepts a target, it disappears from the game area, but its path is still computed until it hits the perimeter and a new object can be created.

Points are earned after each successful interception with some objects earning more points than others. The point value of each object is sampled from a uniform distribution and is represented by the degree to which an object has orange fill (rather than blue). Because the objects continue on their path until they exit the playable area, the player must make strategic decisions about which objects to prioritize for interception. Thus, the player should plan interception paths to maximize the score across all objects.

3.3 Design

Overall, the experiment was structured as a 2×2 between subjects design varying the absence or presence of AI assistance across the first and second block of the experiment. The four conditions are shown in Table 1. In Condition A, participants never saw AI suggestions. Participants assigned to Condition B were shown AI suggestions in the first block and none in the second block. Condition C did not show participants AI suggestions in the first block but then showed the AI suggestions in the second block. Condition D always presented the AI suggestions to subjects. Participants were counterbalanced between these conditions.

3.4 Procedure

Participants began with an interactive instruction section that explained each component of game-play to ensure understanding.

Table 1: The presence and absence of AI assistance across the two blocks in four experimental conditions and number of participants (N) assigned to each condition.

	AI Assistance		
Condition	Block 1	Block 2	N
A	OFF	OFF	48
B	ON	OFF	48
C	OFF	ON	45
D	ON	ON	48

After a sequence of comprehension checks, participants were then directed to the main experiment.

In the main experiment, participants completed two blocks which consisted each of two separate rounds, leading to a total of four rounds of game-play. Each round lasted four minutes leading to 16 minutes of total game-play in the study. During each round of a block, an icon of a robot was shown on the right-hand side of the game screen, indicating the status of AI assistance. In blocks where the AI assistant was off, the robot's image became transparent and text informed the user that it was not currently offering suggestions, and vice versa. A counter displayed on the upper-right section of the game screen showed participants their current score in a round. After completing a single block, participants were directed to a survey where they answered questions on a seven-point Likert scale. After completing a block where the AI assistance was off, participants answered a three question survey assessing the workload of the task (e.g. How hard did you have to work to accomplish your level of performance?). After completing a block in which the AI assistance was on, participants answered nine survey questions, including the three workload questions (same as in the AI assistance off condition), three usability questions, and three teaming questions. See Table 2 for a summary of the survey questions. Following these questions, participants answered an open-ended question asking for feedback about how well the AI algorithm functioned as an assistant.This survey was designed to collect subjective feedback on the participants' experiences during the game. The insights gathered from these questionnaires help to understand the human aspect of human-AI collaboration and to assess the effectiveness of the AI assistants in enhancing player performance and experience.

3.5 AI Assistance

During the game, an AI assistant was calculating path suggestions in real-time taking into account the player's position, the object positions, as well as the direction and velocity of object movements. The AI is based on a search algorithm that searches the combinatorial space of repeated object interceptions for all plans that involve up to three objects. For some interception sequences, a particular object would be unreachable, thus terminating the interception sequence. For each sequence, a total value is calculated by the sum of the point values of the objects intercepted. The final suggestion is based on the interception sequence with the highest total value. Note that although the algorithm plans the interception sequence over the next three objects, the AI suggestion presented to the participant only consisted of the first move of the sequence (see Figure 1). In the actual game, the suggested path was highlighted with a yellow line to a marked position from the current player's position to this suggested location. The suggested points were updated in real-time as the player was moving in the game area.

Note that the planning algorithm is not an optimal algorithm for two reasons. First, the planning depth was limited to interception sequences of length three to allow for real-time updates of AI assistance while the participant was engaging in the task. Second, the planning algorithm uses a heuristic to take into account the possibility of future objects entering the scene. When planning for the first, second, and third interception, the algorithm discounts the value of future interceptions by a factor of α^K where K is the estimated number of new objects that will enter the scene by the time a new interception is planned and α is a discounting parameter. Simulations determined that $\alpha = 0.9$ led to performance levels adequate to outmatch most people.

Pilot studies showed that initial versions of this AI assistance appeared overly erratic to participants. As new objects would come into the scene, the AI assistant could quickly abandon the previous interception plan and change to a new plan. In our pilot studies, these rapid suggestion changes were perceived as somewhat disruptive and difficult to follow. To address this limitation, we introduced a *stability* parameter where the assistant only changes the current suggested plan when the new plan is at least 20% better than the current one. The 20% threshold was chosen based on pilot studies that found that assistance with smaller thresholds was perceived as erratic while assistance with larger thresholds was seen as overly rigid and inflexible. As a consequence of adding this stability threshold, the AI algorithm's performance (when the algorithm would play independently) slightly decreases (by about 10%). Nonetheless, the addition of this stability component leads to AI assistance being somewhat easier to follow while still leading to high performance (if followed).

3.6 Data analysis

3.6.1 Relative Performance Scoring. To evaluate the performance of each participant, we calculated a percentage score of the point value obtained by the participant relative to what the path planner algorithm obtained if that algorithm would play the same game without the human player present. This was calculated by computing another instance of the path planner algorithm with the same game environment and object sequence. Thus, this second instance was playing the game in the background independent from the participant. We calculated the relative score at the level of rounds in order to arrive at performance metrics situated at a sensible midpoint between granularity and variability.

4 RESULTS

4.1 Practice Effects

Figure 2 shows the relative performance scores across conditions and time. To elucidate learning effects across rounds within conditions, we computed a linear mixed model with the fixed factors of round, condition, as well as the interaction between round and condition. Additionally, the participant identifier was specified as a

Table 2: Questions from the survey section

Metric	Questions
Workload	How mentally demanding was the task? How successful were you in accomplishing what you were asked to do? How hard did you have to work to accomplish your level of performance?
Usability	I think that I would like to use this AI assistant frequently. I thought the AI assistant's suggestions were easy to use. I thought there was too much inconsistency in this AI assistant.
Teaming	The AI assistant is contributing to the success of the team. I understand the AI assistant's intentions. I felt very confident using the AI assistant.

random factor in the model to control for the performance levels of participants. We subjected this model to a series of Holm-corrected paired contrast tests to establish performance differences in the time series. Overall, the results show that performance improves by practice with the task, asymptotic during the third round for conditions A and D, $t(2823) = -1.964$, $p = .10$; $t(2823) = 0.203$, $p = .914$ (all previous comparisons $p < .001$). The learning effects across conditions support the notion that there are different aspects of performance that are improved by practice, including the ability to plan specific interceptions, plan for multiple interceptions as well as follow the AI suggestions.

4.2 Performance Differences

The results in Figure 2 show that performance was generally better with AI assistance than without AI assistance. For example, there was about a 10% performance difference between condition D (always AI assistance) and condition A (no AI assistance). Indeed, we find a statistically significant difference in the performance levels between conditions A and D, after performing contrast tests on a linear mixed model with a fixed factor of condition and a random factor for participant identifier, $t(185) = -3.254$, $p = .008$.

In addition, using the same model specified in section 4.1 with a different set of contrasts we can show that for condition B the initial learning with the AI in the first block (i.e., first 8 minutes) led to a loss in performance in the next block when participants had to perform the task on their own, $t(2823) = 2.885$, $p = .024$. However, performance in the second block of condition B was not significantly better than the second block of condition A, showing that AI assistance did not lead to the transfer of new skills to the participants, $t(198) = .039$, $p = .522$. Furthermore, there is only a strong trend towards the independent performance in the second block of Condition B being better than the first block in Condition A, $t(198) = .142$, $p = .062$. Thus, there is insufficient evidence to suggest that players implicitly learned from the assistant in a manner that outlasts the presence of this assistance. Conversely, participants also did not appear to offload all of their cognitive processing onto the assistant, as doing so would have meant regressing to performance levels observed in the first block of condition A, suggesting task learning was not diminished by task assistance.

4.3 Adherence to AI

We perform a more detailed analysis on player clicks to understand how participants' game-play strategies were influenced by AI suggestions. Each time a player clicked to pursue a target, we calculated the pixel distance to the AI-suggested click position. This distance was calculated regardless of whether the AI suggestion was actually shown to the user or was simply calculated in the background. In addition, we computed the proportion of cases where the particular target suggested by the AI algorithm (at the time the participant clicks) was successfully intercepted by the participant. Figure 3 shows that participants were partially successful in implementing the AI suggestions. Participants captured between 70% and 80% of the targets suggested by the AI algorithm and were, on average, off by 60-80 pixels (for comparison, the diameter of the circular play area is 800 pixels). In the conditions where AI assistance was provided, participants who deviated more from the AI suggestions (in terms of average pixel distance) performed significantly worse on average (one-way ANOVA, $F(1,140)=14.2$, $p<.001$). One explanation for this individual difference effect is that some participants may have attempted to follow the advice but responded too slowly and did not click close enough to the suggested location and thus missed the intended target. Furthermore, some participants may have ignored the AI suggestions, resulting in no benefit from the AI assistance.

4.4 Perceived workload

Figure 4 shows the mean rated workload separated by condition and block. Overall, workload was given moderate ratings (mean values between 3.5 and 4.5 on a seven-point scale). The results show a trend that workload was slightly lower with AI assistance than without AI assistance. Results also show that workload increased in the second block with the exception of Condition C where there was a small trend for workload to decrease. However, in general, there were no strong effects of condition on perceived workload, with a two-way ANOVA, showing no effect of workload across conditions, $F(3,556) = 1.739$, $p = .158$, insufficient evidence for an effect of block, $F(1, 556) = .9$, $p = .343$, as well as the interaction between condition and block, $F(3, 556) = .581$, $p = .627$.

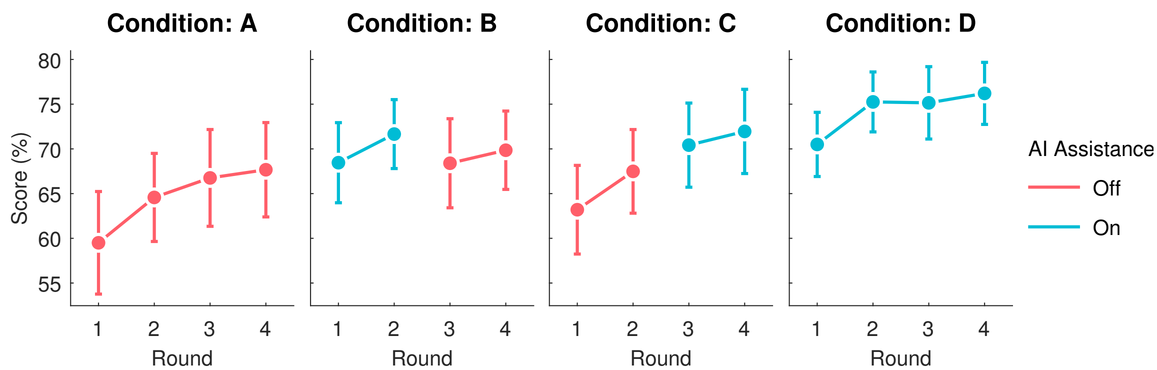

Figure 2: Performance scores over rounds by condition and AI assistance. Performance is expressed as a percentage of the score relative to the score achieved by the path planner algorithm that independently performs the task. Error bars represent the standard error of the participant mean. Note that there are transitions between blocks (including the end of the game) that involve a corresponding survey to condition pairing.

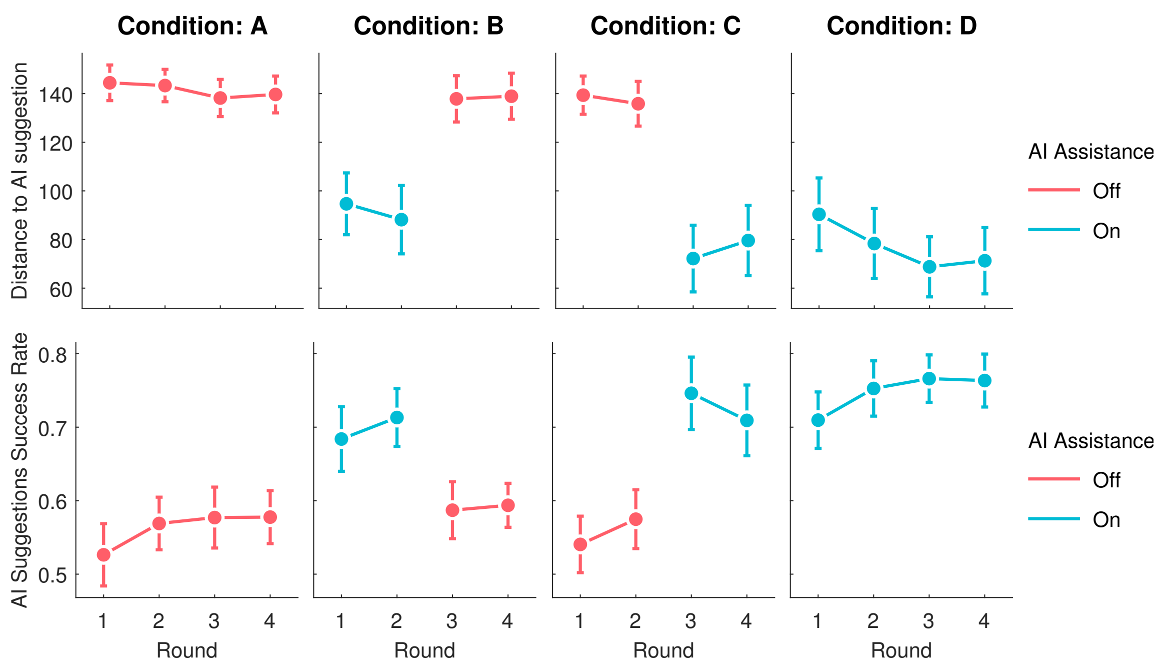

Figure 3: Influence of AI suggestions of behavior across conditions and rounds: mean distance of the participants' clicks and the AI suggested locations (top row) and the proportion of successfully intercepted target suggested by the AI (bottom row). Error bars represent the standard error of the participant mean.

5 DISCUSSION

This study aimed to understand whether AI assistance serves as an expert teacher or is used as a dependence-inducing "crutch". If AI assistant was an expert teacher, then we would see that exposure to it initially would lead to significantly better performance than if one had not been exposed. However, our analysis of the ordering of AI assistance indicated no transfer of learning effect. As a result, AI assistant could not be considered an expert teacher in this game environment.

Conversely, if participants were overly-reliant on AI assistance then participants who had been exposed to AI assistance first would have performed similarly to those having no previous experience with the game. Our results showed that players do not regress to the lower performance found in naive players but are also not significantly better than naive players. Consequently, we were unable to find evidence of over-reliance in our experiment. One possible reason this lack of substantive skill extinction did not occur may relate to the nature of the task. More specifically, it could be that the game's reliance on more low-level, perceptual decision-making,

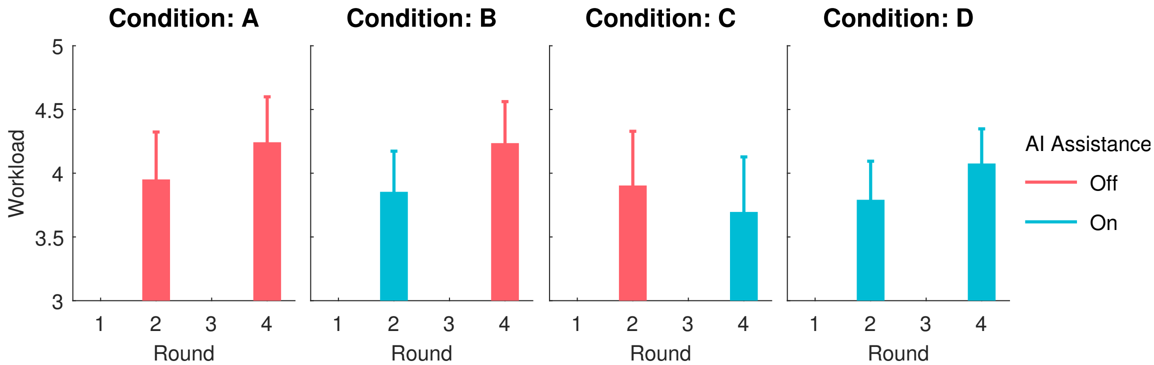

Figure 4: Mean rated workload at the end of the first block (round 2) and second block (round 4). Error bars represent the standard error of the participant mean.

reduced the need for offloading of cognitive effort onto the assistant. If this is indeed the cause, one would expect tasks with significant high-level, strategic components to induce a much greater degree of over-reliance, as cognitively demanding processing steps can be conveniently bypassed with an assistant.

5.1 Limitations and Future Work

Open-ended feedback from participants showed that the AI assistant lacked some strategies humans view as optimal. One specific example is the ability to reason about a cluster of targets as a single valid intercept location with a cumulative value. The strength of this strategy lies in the possibility that the sum of a cluster's value would yield more value than intercepting the first target from the path planner. Thus, some participants felt that the AI negated their strategy and may be guided by a worse understanding of the game. One way to alleviate this strategic gap is for the AI assistant to suggest interception sequences that target not only individual targets but also clusters of targets.

Additionally, open-ended feedback indicated that some participants felt the AI was cognitively demanding and confusing. However, results from the workload questionnaires did not reflect this sentiment: having AI assistance does not strain workload at the group level (see Figure 4). Future work could assess individual differences in performance and workload to determine which participants are most capable of integrating AI assistance in this environment. To enhance the detection of individual differences, behavioral measures such as the Detection Response Task, a task commonly used to assess cognitive load in driving scenarios [21], can augment our survey measures of cognitive load. This analysis can then motivate an adaptive framework for AI assistance that provides the type of assistance that a particular person can most benefit from.

Finally, future experiments can also vary the difficulty of the task by varying the number of moving objects in the game environment. These experiments can highlight the specific circumstances under which humans benefit most from AI assistance. For example, there may be an interaction between task difficulty and the benefits derived from AI assistance — people may be more likely to defer to AI suggestions in high workload scenarios.

6 CONCLUSION

In sum, we set out to evaluate the veracity of claims portraying AI assistance in different lights, one related to enhanced learning, and one contrasting view concerned with risks of diminishing autonomy and skills through AI dependence. Interestingly, we were unable to find strong support for either claim, suggesting that there are situations in which AI assistance can boost human performance without impacting learning positively nor negatively. This observation provides compelling support for the notion that cognitive tasks that humans can perform with relative automaticity, but are not yet fully automatable, can be boosted with AI assistance without significant risk to independent human performance. This may prove highly relevant to assisted driving and other contexts that require humans to have a final say on decisions.

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